CROSS-PRODUCT COMPATIBILITY, LOCK-IN, AND MARKET POWER: THE CASE OF SMARTPHONES AND LAPTOPS

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This paper examines how compatibility across *standalone* technology products creates lock-in and cross-market power. Using an experiment, I identify the causal effect of compatibility: willingness to pay for a smartphone rises by 9% of the retail price when it is compatible with a laptop. I use this to discipline a structural smartphone-demand model that incorporates compatibility, and evaluate the effects of *(i)* mandating cross-brand compatibility ("open ecosystems") and *(ii)* cross-market mergers. Open-ecosystem effects vary with the Apple–Samsung hardware-quality gap, but mean consumer surplus rises in every period. A counterfactual Samsung–HP merger lowers smartphone market concentration yet raises Samsung prices, disadvantaging consumers who value compatibility less.

KEYWORDS: compatibility, lock-in, market power, cross-market mergers, ecosystems, demand estimation, incentivized experiments.

"Tie all of our products together, so we further lock customers into our ecosystem" (Steve Jobs, former Apple CEO).

1. INTRODUCTION

In March 2024, the Department of Justice (DOJ) filed a lawsuit against Apple under Section 2 of the Sherman Act, alleging that the firm locks consumers into its ecosystem. In the European Union, similar concerns have led the European Commission, through the Digital Markets Act, to require Apple to provide third parties with effective interoperability with iPhone operating-system features that support cross-device interaction, data transfer, and device setup (European Commission, 2026). These regulatory actions raise a critical question: What are the welfare effects of mandating cross-brand compatibility (i.e., "open ecosystems") for non-substitute standalone technology products, such as smartphones and laptops?[1][2] The effects of such mandates are ambiguous. Open ecosystems can enhance product variety, reduce switching costs, and increase consumer surplus by allowing consumers to benefit from cross-product compatibility without being locked into a single ecosystem (Farrell and Klemperer, 2007). However, such mandates may also weaken firms' incentives to invest in interoperability and may raise prices if demand expansion exceeds competitive pressure, diminishing surplus for consumers who value compatibility less (Matutes and Regibeau, 1988, Katz and Shapiro, 1985, Chen, Doraszelski,

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[1] I use "standalone" products to refer to products that can be purchased and used independently, rather than as components of a single integrated bundle. Smartphones and laptops are standalone because each has independent functionality, even though compatibility between them can generate additional value.

[2] Compatibility across brands is first shown to be possible in 2021, when Apple allows FaceTime to connect with non-Apple smartphones and laptops.

and Harrington, 2009).[3] Additionally, open ecosystems could increase smartphone market concentration by enabling non-Apple laptop users to purchase Apple smartphones while retaining cross-product benefits, reinforcing Apple's dominance and potentially leading to higher prices.

As cross-product compatibility becomes increasingly significant, cross-market mergers that affect compatibility may influence demand and market concentration. However, regulators often overlook these mergers, viewing them as relevant only to individual product markets (e.g., the DOJ's 2014 report on Lenovo's acquisition of Motorola). This raises a critical question: What are the welfare effects of a cross-market merger in the presence of cross-product compatibility externalities? The effects of such mergers are ambiguous. They can enhance compatibility and reduce double marginalization by boosting demand in complementary markets (Song, Nicholson, and Lucarelli, 2017, Ershov, Laliberté, Marcoux, and Orr, 2025). Conversely, the merged firm may exploit locked-in consumers by raising prices and limiting compatibility with competitors, thereby reducing product variety and consumer surplus.

Combining experimental and observational data, I evaluate the impact of smartphone–laptop compatibility on smartphone demand and competition. I first establish the causal effect of compatibility on demand using a novel incentivized experiment that follows Becker, DeGroot, and Marschak (1964) to elicit willingness to pay (WTP) for a smartphone conditional on receiving a laptop. I use this evidence to construct a smartphone demand and supply model incorporating compatibility with laptops. I estimate the model using repeated cross-sectional market data from the International Data Corporation (IDC) Tracker (2018–2023), a proprietary compatibility index, a product-ownership survey that I administer, and experimental WTP evidence. The experimental evidence enters the estimation through a micro-moment that matches the model-implied WTP gain from compatibility to its experimental counterpart.[4] I then use the estimated model to evaluate two counterfactuals: an open-ecosystems policy that mandates cross-brand compatibility, and a merger between Samsung, which primarily operates in the smartphone market but holds a 3% share in the laptop market, and HP, the leading laptop manufacturer—both key competitors of Apple.

The experiment and survey serve four purposes. The survey reveals the cross-ownership patterns needed to link smartphone and laptop markets, since cross-sectional market data do not connect consumers' choices across the two markets. It also supplies two model inputs: a smartphone market-size estimate from purchase recurrence and a non-parametric distribution of consumer characteristics. The experiment, in turn, provides a direct measure of WTP for compatibility that cannot otherwise be disentangled from same-brand preferences and brand loyalty. Finally, the survey establishes two stylized facts: agents participate in one market at a time, and smartphone buyers are myopic about future laptop costs.

The experiment identifies a significant causal effect of compatibility on smartphone demand. It elicits willingness to pay in an incentivized setting in which the price is randomly drawn and purchase is contingent on winning a laptop lottery, making truthful reporting a weakly dominant strategy. Among participants who report no prior knowledge of compatibility and receive no information, the average WTP difference between compatible and incompatible smartphones is only $7 and is insignificant; participants who report some prior knowledge already assign significantly higher WTP, so this muted gap reflects limited information rather than the absence of value. I therefore also elicit WTP after providing standardized compatibility information. This informed condition aligns the elicited valuations with the structural model, which, like standard discrete-choice demand models, treats the characteristics entering utility as observed

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[3] I leave the effect of open ecosystems on innovation incentives to future work.

[4] For an overview of merging experimental results with structural models in the labor economics literature, see Todd and Wolpin (2023).

by consumers. It reflects the information environment of an actual purchase, since buyers of durable, high-cost goods inform themselves beforehand and a random sample, rather than those actively shopping for a smartphone, would otherwise understate these valuations. Under this condition the WTP difference rises to a significant \$75 (9% of the retail price, $p < 0.01$). As a validation exercise, I later compare this magnitude to market prices for third-party services that provide partial cross-device compatibility.

The estimated model attributes smartphone demand to both standalone hardware characteristics and compatibility with owned laptops, consistent with the experimental evidence.

Using the estimated model, I evaluate an open-ecosystems counterfactual in which any smartphone-laptop pair is potentially compatible. The results show that in 2018–2019, when Apple's smartphones significantly exceed Samsung's in hardware quality, closed ecosystems benefit Samsung. This is because non-Apple laptop owners are locked into lower-quality Samsung smartphones. Open ecosystems induce non-Apple laptop owners to switch to Apple smartphones, increasing market concentration and boosting Apple's profits while reducing competitors' profits. However, from 2020 to 2023, the closed ecosystem benefits Apple as the hardware quality gap narrows. Open ecosystems induce Apple laptop owners to switch to Samsung smartphones, as compatibility remains constant while Samsung's top devices exceed Apple's hardware quality. In both time frames, mean consumer surplus increases due to a broader variety of compatible products and intensified competition that can lower prices.

I further examine the role of compatibility by evaluating a counterfactual of a cross-market merger between Samsung and HP, with the merged entity benefiting from enhanced compatibility. The merger boosts Samsung's smartphone share at Apple's expense, lowering smartphone market concentration; despite this, Samsung's price rises, driven by the cross-market power that ties consumers to its ecosystem. Although the merger raises mean consumer surplus, the rise in the merged entity's prices reduces the surplus for those who value compatibility less. The profit-maximizing compatibility policy maintains a lower, but positive, level of compatibility with rival non-Apple laptop producers, preserving purchases by non-Apple laptop owners while maintaining a stronger compatibility advantage for Samsung–HP pairs.

This paper contributes to four strands of literature. First, it advances the growing empirical literature on open ecosystems. Prior work has largely examined add-on products, where incompatibility results in exclusion from consumers' consideration sets, finding varied effects on welfare (Lee, 2013, Huang, 2022, Li, 2023). In contrast, standalone products—such as smartphones and laptops—retain value even when incompatible, with compatibility influencing whether and how consumers incorporate products into their decision-making. I extend this literature by studying standalone products whose value does not vanish when incompatible, introducing a non-binary compatibility index that enters utility directly, and showing how laptop ownership shapes smartphone demand through cross-product complementarities (cf. Gentzkow, 2007).[5,6]

Second, this paper contributes to the literature on cross-market mergers by studying a merger whose effects operate through compatibility between standalone products. Existing empirical work shows that cross-market mergers can have ambiguous price effects when firms internalize demand spillovers across markets (Song, Nicholson, and Lucarelli, 2017, Ershov, Laliberté, Marcoux, and Orr, 2025, Wang, 2021). I show that compatibility creates a distinct source of

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[5] For further discussion on distinguishing unobserved heterogeneity from state-dependent preferences, see, for example, Pakes, Porter, Shepard, and Calder-Wang (2021), which develops a choice model incorporating state dependence while allowing for unobserved heterogeneity in individual-good fixed effects.

[6] This analysis relates to recent theoretical work on ecosystem-driven utility and cross-market firm power (Heidhues, Kösters, and Kîoszegi, 2024), though the focus here is on the demand-side implications of compatibility.

cross-market power: the merged firm can raise the value of its own ecosystem while limiting compatibility with rivals. This channel is especially relevant in technology markets, where ecosystem design links products that antitrust analysis often treats separately.

Third, this paper contributes to the empirical literature on digital markets (Goldfarb and Tucker, 2019), and particularly on the sources of market power within them. One strand studies digital *platforms*, showing how network effects, consolidation, and platform design shape market power (Farronato, Fong, and Fradkin, 2024, Kaye, 2024). A second strand provides rich demand estimates for digital *products* within individual markets (e.g., Goeree (2008), Eizenberg (2014) for personal computers; Fan and Yang (2020) for smartphones). In closely related work, Bursztyn et al. (2025) shows that Apple's ecosystem design shapes smartphone demand, identifying a channel of ecosystem-driven market power. Building on these strands, this paper studies smartphones and laptops in tandem and shows that their demand is interdependent through compatibility, carrying the analysis of market power in digital markets across the boundary between two product markets.

Fourth, the paper makes a methodological contribution by showing how an incentivized experiment can discipline a structural demand model, separating causal compatibility effects from correlated brand preferences—a distinction that market data alone cannot identify (Pakes, 2021). In doing so, it joins a literature that uses experimental variation to identify structural parameters, as Dubé, Hitsch, and Jindal (2014) separate utility from the discount factor, two objects that choice data alone cannot disentangle.

The remainder of the paper proceeds as follows. Section 2 presents the experiment identifying the causal effect of compatibility on demand. Section 3 introduces the observational data used to estimate the structural model: the compatibility index, the repeated cross-sectional market data, and the survey. Section 4 presents the model; Section 5, the estimation approach and results; and Section 6, the counterfactual analysis.

2. EXPERIMENT: IDENTIFYING COMPATIBILITY

Consumers often purchase and use smartphones and laptops as standalone devices, which may suggest that brand choices across markets are merely correlated or driven by same-brand preferences and loyalty. However, such patterns—choosing a smartphone brand to match an already-owned laptop—may instead reflect a causal effect of compatibility on purchasing decisions.

I design an incentivized experiment to examine whether compatibility influences demand for standalone goods and to estimate participants' valuation of compatibility. The experiment randomly assigns participants to a lottery for an Apple or Samsung laptop and a cash prize equal to the smartphone's retail price. It then elicits their WTP for an Apple or Samsung smartphone using the Becker–DeGroot–Marschak mechanism (Becker, DeGroot, and Marschak, 1964). The lottery is resolved after the experiment, and the reported WTP determines whether the lottery winner keeps the cash prize or purchases the smartphone at a randomly drawn price, keeping the remaining cash. By varying the laptop brand, which directly affects cross-device compatibility, the experiment identifies the causal effect of compatibility on smartphone WTP.

2.1. *Consumer decision*

Consider consumer i, who owns laptop c and evaluates smartphone $j \in S$. Consumer i's utility from purchasing smartphone j at price p_j while owning laptop c is quasi-linear,

$$u_{ijc} = V_{ij} + W_{ijc} - p_j, \tag{1}$$

where V_{ij} is utility from smartphone j's independent characteristics (e.g. screen size) and W_{ijc} is utility from the interaction between smartphone j and laptop c. Willingness to pay is the price that leaves consumer i indifferent between buying and not buying, so that

$$\mathrm{WTP}_{ijc} = V_{ij} + W_{ijc}. \tag{2}$$

I decompose

$$W_{ijc} = w_{ijc} + F_{BM}, \tag{3}$$

where w_{ijc} reflects functional compatibility (e.g. copy–paste across devices) and F_{BM} is a brand-matching fixed effect that captures the additional utility from owning two devices produced by the same firm. By construction, V_{ij}, w_{ijc}, and F_{BM} are additively separable.[7]

When smartphone j is compatible with laptop c but not with laptop c', compatibility contributes $w_{ijc} > 0$ while $w_{ijc'} = 0$. Similarly, if the devices are produced by the same firm, the brand-matching fixed effect is $F_{BM} > 0$; otherwise $F_{BM} = 0$.

Because $\mathrm{WTP}_{ijc} = V_{ij} + w_{ijc} + F_{BM}$ and $\mathrm{WTP}_{ijc'} = V_{ij}$ by construction, the willingness-to-pay difference satisfies $\mathrm{WTP}_{ijc} - \mathrm{WTP}_{ijc'} = w_{ijc} + F_{BM}$, so the monetary value of w_{ijc} is obtained once the brand-matching premium F_{BM} is identified. I identify F_{BM} by comparing willingness to pay for smartphones when consumed with same-brand versus different-brand laptops among participants who are not aware of any compatibility features. Because these participants cannot attribute value to functional compatibility, any difference in their willingness to pay reflects only brand matching. The decomposition of W_{ijc} into w_{ijc} and F_{BM} therefore allows the empirical analysis to separately identify (i) the value of functional compatibility and (ii) the value of brand matching.

2.2. *Experiment design*

To establish a baseline WTP for smartphones and to assess the role of owned laptops, the experiment first asks participants to state their WTP for Apple and Samsung smartphones through purely stated preferences, without a lottery. Participants who value compatibility can condition their WTP based on the connectivity with their existing laptops. However, since participants' owned laptops are not randomly assigned, this introduces potential state confounding. To address this, I subsequently randomize product ownership by introducing a lottery for a laptop and a monetary prize. Only a lottery winner can purchase a product (depending on their WTP, as explained hereafter) and control product use (whether participants keep or sell), ensuring independence between previously owned laptops and WTP for smartphones.

The experiment is structured as a series of WTP elicitations. Participants can win a laptop and a cash prize equivalent to the smartphone's retail price (*RP*). Since the design uses a random sample rather than individuals intending to purchase smartphones—expensive durable goods—the experiment endows participants with a cash prize. Participants use the cash prize to offer a price from \$0 to $\$RP$ for a smartphone. After the experiment, I draw a random price, *p*, between zero and the smartphone's RP. Payoffs follow Equation (4). Participants see identical WTP questions, with the elicitation order randomized to avoid order effects, where earlier

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[7] Additive separability provides the minimal structure consistent with the experimental variation. A multiplicative form, $V_{ij} \times W_{ijc}$, would make compatibility mechanically more valuable for phones with larger screens or better cameras, and $w_{ijc} \times F_{BM}$ would imply no same-brand premium absent compatibility, contradicting participants who are unaware of compatibility yet still report higher WTP for same-brand products.

questions might influence responses to later ones.

$$\text{payoff} = \begin{cases} \$4, & \text{if not winning the lottery;} \\ \$4 + laptop + \$RP, & \text{if win the lottery \& WTP} < p; \\ \$4 + laptop + smartphone + (\$RP - \$p), & \text{if win the lottery \& WTP} \geq p. \end{cases} \tag{4}$$

The reported WTP only determines whether, in addition to a laptop, the participant's payoff is \$RP or smartphone + (\$RP - \$p). Because the cash prize (\$RP - \$p) depends on the randomly drawn price, *p*, rather than the reported WTP, this modification of the Becker, DeGroot, and Marschak (1964) mechanism is incentive-compatible: truthful reporting is a weakly dominant strategy.[8] The instructions explain this property to participants using examples that do not involve smartphone purchases, to avoid anchoring their offers.

Because the laptop lottery and the random selection of a single WTP question for payment are resolved only after the experiment, participants must treat each elicitation independently and as if they win the lottery. This procedure adapts the mechanism of Coffman and Niehaus (2020).

Because the laptop is awarded for free and at random, its standalone value enters the participant's payoff regardless of the reported smartphone valuation. Randomization removes selection into laptop ownership. Goods vary throughout the experiment, but the selected products have identical retail prices—\$999 for Apple and Samsung laptops and \$799 for smartphones—so the common laptop price equalizes any wealth effect across arms. Participants observe only these prices and receive no information about hardware characteristics (V in Equation 2), so they have no basis to infer hardware-quality differences across laptop brands. Varying the laptop brand in the lottery while holding the offered smartphone, retail prices, and hardware information fixed therefore shifts compatibility between the assigned laptop and the offered smartphone. The empirical analysis controls for the same-brand component captured by F_{BM}. Section 2.3 formalizes the identification and estimation strategy used to isolate the effect of compatibility on WTP.

Because the experiment uses a random sample rather than individuals already planning to enter the smartphone market, participants may be less familiar with smartphone attributes. To approximate the information environment of consumers actively participating in the smartphone market, and to align the experimental measure with standard demand models in which product characteristics entering utility are observed by consumers (e.g., Berry, Levinsohn, and Pakes, 1995, Nevo, 2001), the WTP elicitation segment concludes by providing standardized information on smartphone-laptop compatibility features before eliciting their offers. This design follows the logic that experimental measures of WTP are more likely to reflect informed, market-relevant preferences when respondents are provided with relevant product information and face a choice setting that resembles market decision-making (McFadden, 1998). It is also similar in spirit to experiments that provide consumers with product information or product exposure before eliciting willingness to pay and then use the resulting evidence to study demand (e.g., Berry, Fischer, and Guiteras, 2020, Bursztyn et al., 2025).[9]

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[8] More recently, the mechanism is used to elicit WTP for clean water in Ghana (Berry, Fischer, and Guiteras, 2020) and willingness to accept compensation for deactivating Facebook (Allcott, Braghieri, Eichmeyer, and Gentzkow, 2020).

[9] Allcott and Taubinsky (2015) similarly provide hard product information before eliciting WTP and use the resulting responses to discipline a model of consumer behavior, while acknowledging that the resulting valuations are a useful approximation of valuations under full information.

The compatibility information provided includes the ability to call and text from a laptop, copy-paste across devices as if they were one device, and automatically connect to a smartphone hotspot from a laptop. To control for participants' prior knowledge, the experiment asks whether they are aware of connectivity characteristics beforehand.

One concern is that participants may interpret each additional piece of compatibility information as inherently positive and raise subsequent offers—an anchoring effect between the question set without compatibility information and the subsequent set with it. To test for this effect, participants are randomly assigned either to answer WTP questions first without and then with compatibility information, or only with it.

Incentives are large relative to a recent Prolific benchmark (Exley and Nielsen, 2024), and comprehension questions verify that participants understand the payoff consequences of reporting a WTP below or above the randomly drawn price (Supplemental Appendix, Section S.1). Because each WTP question is equally likely to be selected for payment, the low payment probability does not differentially affect compatible versus incompatible products, or questions with versus without compatibility information. Any difference in WTP therefore reflects compatibility.

2.3. *WTP estimation*

I estimate the effect of compatibility on participants' WTP for smartphones using two measures: within-subject and across-subject comparisons. I present the within-subject results; the across-subject estimates are qualitatively similar. Because participants are randomly assigned the same set of questions, conditional on whether they provide WTP both without and with compatibility information or only with it, identification of the compatibility effect is straightforward in both cases. I compare WTP for compatible and incompatible smartphones, both within and across individuals, controlling for the brand-matching component F_{BM} defined in Section 2.1. The corresponding indicator equals one when the smartphone and laptop share a brand, regardless of actual compatibility, and captures brand-related utility not driven by compatibility, such as interface familiarity and perceived quality consistency. Controlling for this component ensures that the estimated WTP difference isolates the causal impact of cross-product compatibility.

2.4. *Recruitment*

Participant recruitment is conducted in accordance with the pre-analysis plan: participants are recruited through the online platform Prolific, which provides a diverse and heterogeneous sample of the U.S. population and is increasingly used in social science, particularly in experimental economics (Palan and Schitter, 2018, Allcott et al., 2024, Bursztyn et al., 2025). In January 2024, I randomly recruit 1,000 agents who previously completed at least a thousand tasks on Prolific.[10] Sample details are presented in Table I. The experiment sample is, on average, three years younger, has an income that is \$7,000 higher, one year more educated, and 12% less female compared to the 2022 mean from the Current Population Survey (CPS).

The experiment lasts an average of 20 minutes, and participants receive a base payment of \$4, equivalent to \$12 per hour and substantially higher than Prolific's \$8 hourly minimum, along with any prizes they win. This pool of participants, along with an additional 119 respondents who do not take part in the experiment, also answer the survey described in Section 3.3.

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[10] Due to Prolific's data-recording error, I use only 992 participants. The results are insensitive to this.

TABLE I

DEMOGRAPHIC DESCRIPTIVE STATISTICS

Category	Mean	SD	Min	Max
Age	40.65	10.46	20.00	67.00
Income	\$59,090.90	\$41,518.14	\$2,500.00	\$150,000.00
Education	14.97	2.16	10.00	20.00
Gender	Male = 588, Female = 394, Prefer not to say = 10			

TABLE II

WTP WITHOUT AND WITH COMPATIBILITY INFORMATION CONDITIONAL ON PRE-KNOWLEDGE STATE

			Panel A: WTP without compatibility information			**Panel B: WTP with compatibility information**		
Smartphone brand	Compat. pre-know.	N	Mean WTP compat.	Mean WTP incompat.	Mean diff.	Mean WTP compat.	Mean WTP incompat.	Mean diff.
Apple	✗	263	413.92 (241.95)	405.01 (243.72)	8.90*	431.84 (238.61)	356.49 (222.87)	75.34***
Samsung	✗	363	393.87 (239.87)	387.86 (244.05)	6.00	416.67 (233.98)	341.89 (232.35)	74.77***
Apple	✓	630	504.96 (226.59)	487.43 (228.33)	17.52***	521.07 (219.59)	415.80 (220.17)	105.27***
Samsung	✓	530	489.80 (214.59)	471.79 (218.59)	18.01***	497.72 (214.49)	413.62 (211.32)	84.09***

Note: Compatibility pre-knowledge ✗ and ✓ indicate that after the experiment, participants reported they previously did not and did know about compatibility features, respectively. Standard deviations are in parentheses. Statistical significance is denoted as: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

2.5. *Experiment results*

The first WTP elicitations, asked without the lottery, are purely stated preferences. Consistent with the literature on hypothetical bias (Cummings, Harrison, and Rutström, 1995, List, 2001), stated WTPs exceed incentivized offers, supporting the use of the payment mechanism to elicit payoff-relevant valuations.

Table II, Panel A, presents the WTP results when no compatibility information is provided. For participants who report they do not know (group "✗") about connectivity, the difference in WTP between compatible and incompatible smartphones is \$9 for Apple and \$6 for Samsung, with the difference being significant only for Apple ($p < 0.1$). Following Section 2.1, I interpret this same-brand WTP difference among participants without any compatibility pre-knowledge (not just the information I later provide) as the empirical counterpart of the *'brand matching fixed effect,"* F_{BM}, which is captured as part of the brand fixed effect in the literature. The difference in WTP between compatible and incompatible smartphones for those who profess knowledge about at least one connectivity feature is \$17 for Apple and \$18 for Samsung, where these differences are significant ($p < 0.01$). This suggests that compatibility has positive value even for partially informed participants before any experimenter-provided information; if these participants had full prior knowledge, providing connectivity information should not affect their WTP, but Panel B shows otherwise.

Table II, Panel B, presents WTP after compatibility information is provided, controlling for participants' pre-knowledge state. Relative to Panel A, both groups exhibit a larger compatible–

incompatible WTP difference. Within each brand, the absolute difference is larger for participants with compatibility pre-knowledge than for those initially disclosing ignorance, although the percentage difference is similar across groups. Difference-in-difference analysis across knowledge states shows that this gap is significant for Apple ($p < 0.01$) but not for Samsung, as discussed below.

The larger Apple difference partly reflects auxiliary selection: participants who own an Apple product have higher WTP for Apple smartphones, consistent with stronger Apple-brand preferences among Apple owners and greater familiarity with Apple connectivity features (Supplemental Appendix, Section S.1).

Table II compares WTP with and without compatibility information. Within each prior-knowledge group, information raises WTP for compatible smartphones and lowers WTP for incompatible ones. For participants previously unaware of compatibility, the decline for incompatible devices is consistent with uncertainty resolution: once compatibility is clarified, they revise downward their valuations for devices that do not provide these features.

Because participants' reports of prior knowledge about compatibility features are unincentivized, the pre-knowledge classification may contain misreporting. I therefore subtract from the informed WTP difference the brand-matching fixed effect measured in each reported-knowledge group, using the two groups' no-information WTP differences as bounds. The resulting WTP for connectivity features is \$79–\$87 for Apple and \$63–\$73 for Samsung.

Figure 1 Panels A and B present the distributions of differences in WTP for compatible smartphones. The median difference is \$50, with 82.66% and 79.64% of participants valuing compatibility with Apple and Samsung positively, respectively.[11] Panels C and D restrict the sample to participants who report keeping the products rather than selling or giving them away, further isolating the value of compatibility in use. In this subsample, the median WTP difference rises to \$89 for Apple and remains \$50 for Samsung, with 88% and 86% of participants valuing compatibility positively, respectively.

2.5.1. *Robustness check: anchoring effect*

To test whether eliciting WTP without compatibility information anchors later reports, I compare participants who answer first without and then with compatibility information to those who receive information immediately. Difference-in-difference analysis shows no significant anchoring effect for either brand (Supplemental Appendix, Table S.III). This supports the interpretation that the WTP differences are driven by compatibility rather than by a design that encourages higher offers for compatible products.

2.5.2. *External validity*

A natural concern is whether the experimental estimate captures the value of compatibility in real markets. Third-party applications connect smartphones and laptops across brands only partially, since operating-system providers restrict APIs and system-level features, leaving many valuable functions tied to the native ecosystem. As a market benchmark, a third-party service such as Pushbullet Pro costs \$39.99 per year, or about \$92 over the 2.3-year ownership cycle (Section 3.3.1).[12] This is close to and slightly above the population-weighted experimental WTP of about \$89. Because Pushbullet Pro provides only partial compatibility, the experimental estimate is broadly consistent with market-based valuations and, if anything, conservative: participants are drawn from a broad population rather than active shoppers and may be less attentive despite the information provided.

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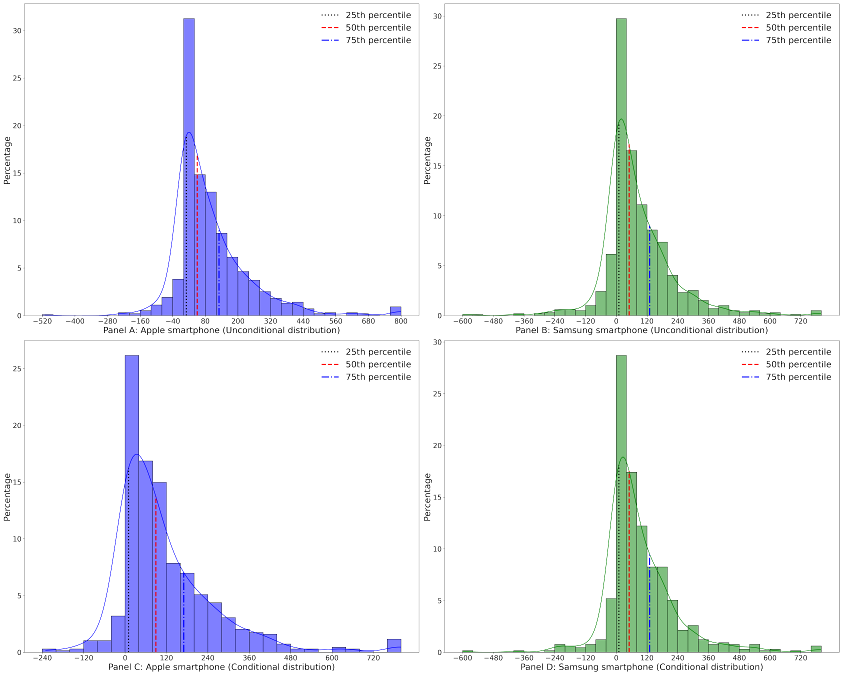
[11] Gender differences in WTP are reported in Section S.2 of the Supplemental Appendix.

[12] See Pushbullet Pro, https://www.pushbullet.com/pro.

FIGURE 1.—The difference in WTP distribution



Note: The figures report WTP distributions for compatible and incompatible Apple and Samsung smartphones. Panels A–B use the full sample; Panels C–D use the subsample of participants who reported retaining the products assigned in the experiment.

2.6. *Experiment conclusion*

The experiment establishes that compatibility causally raises smartphone WTP. Participants with only partial prior knowledge already assign significantly higher WTP to compatible smartphones before any information is provided; under the informed condition, the compatible–incompatible WTP difference is a significant \$75, or 9% of retail price. Reweighted to the population used in the structural model, this is approximately \$29 per feature. Section 4 therefore introduces compatibility directly into utility, and Section 5 uses the experimental WTP difference as a micro-moment.

3. NON-EXPERIMENTAL DATA

The paper uses three data sources to estimate the effect of compatibility on the markets: *(i)* hand collected information on product compatibility from public sources, *(ii)* IDC's Tracker Database, and *(iii)* a survey I conducted.[13] Additionally, the paper incorporates the difference in WTP due to compatibility, as measured in the experiment, as a micro-moment (for more, see section 5). The IDC repeated cross-sectional data enables the estimation of à la Berry, Levinsohn, and Pakes (1995) (BLP) model, i.e., without considering complementarity. The survey incorporates micro-moments, as in Petrin (2002), and provides information on consumer product ownership across multiple markets. By integrating the data on the degree of compatibility

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[13] Eizenberg (2014) employs IDC data.

between smartphones and laptops with the repeated cross-sectional market data and the survey, I can construct a random-coefficient demand model for smartphones, where consumers' decisions are influenced by compatibility with laptops.

3.1. *Compatibility Index*

Apple was the first firm to introduce seamless cross-market connectivity across devices. In October 2013, Apple introduced AirDrop, allowing consumers to transfer files across Apple products. Since then, smartphone and laptop connectivity has evolved to include features such as copy-paste across devices, activating a smartphone hotspot from a laptop, answering phone calls and text messages from a laptop, and typing on a smartphone using a laptop keyboard. While connectivity allows consumers to use one device without physically handling the other, both devices are still required.

I collect data on cross-device compatibility within and across firms from brand websites such as those of Apple, Samsung, and Microsoft. Because producers control and frequently change the system-level interfaces (e.g., APIs) that third-party services use to connect devices (Eaton, Elaluf-Calderwood, Sørensen, and Yoo, 2015), the compatibility those services provide is unstable. This paper therefore limits its attention to pre-installed compatibility features.[14] I include the following compatibility features: file sharing, copy-paste, automatic hotspot, phone call and text, webcam continuity, handoff, casting, camera continuity, and continuity sketch.[15]

Each compatibility feature has a binary outcome. I construct a compatibility index between any two products by summing their binary connectivity features and dividing them by the maximum number of features available in the market at that time.

Apple is only compatible with its products, while Samsung is compatible with many brands using Windows operating system laptops. Compatibility is influenced by both brand and product purchase year. For example, consumers with a 2013 Apple laptop benefit from a compatibility index of 0.6667, while those with a 2019 laptop have an index of 1 with a 2022 iPhone. The sample mean compatibility of Apple products is 0.94, with a minimum of 0.6667 and a maximum of 1. In contrast, Samsung's mean compatibility is 0.01, with a maximum of 0.3333, mainly because of incompatibility with laptops before 2019.

3.2. *Market data*

The market data come from IDC and consist of repeated cross-sections of prices, quantities, and characteristics for model-level smartphones and series-level laptops sold in the U.S. between 2018 and 2023. Average shares in the smartphone and laptop markets are presented in Table III. The smartphone market is highly concentrated, with Apple and Samsung accounting for 77% of sales. Laptop shares are more dispersed across brands, generating variation in consumers' compatibility exposure.

Annual smartphone sales average 123 million units, with a standard deviation of 11 million, and peak at 139 million in 2018. Mean annual sales per model are 1.1 million units, with a

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[14] The European Commission's DMA interoperability measures are broader than the features in this index, but they overlap with several of the same cross-device mechanisms, including file transfer, automatic Wi-Fi connection, media casting, background execution, and other forms of system-level interoperability (European Commission, 2026). I therefore view the index as capturing a subset of the cross-device compatibility channels targeted by current interoperability policy.

[15] Handoff is the ability to switch devices while continuing a task from where one finished. Camera continuity allows consumers to take a picture with the smartphone and view it on the laptop. Continuity sketch involves sketching on a laptop using the smartphone touch screen.

TABLE III

AVERAGE MARKET SHARE OF SMARTPHONE AND LAPTOP BRANDS, 2018-2023

Panel A: Smartphones		**Panel B: Laptops**	
Brand	Share	Brand	Share
Apple	0.50	HP	0.31
Samsung	0.27	Apple	0.27
Motorola	0.08	Lenovo	0.17
LG	0.07	Dell	0.10
Alcatel	0.04	Acer	0.08
Google	0.03	Asus	0.07

TABLE IV

SMARTPHONES CHARACTERISTICS- SUMMARY STATISTICS

Variable	Mean	SD	Min	Max
Prices ($)	483.12	431.59	15.17	1906.94
Screen size (inches)	5.88	0.66	4.00	7.60
Megapixels	22.94	24.26	6.50	108.00
Storage (GB)	105.41	120.34	8.00	597.33
Processor speed (GHz)	2.11	0.52	1.40	2.80
Number of smartphones		636		

standard deviation of 2.3 million. Table IV summarizes prices and hardware characteristics. The dispersion in these variables reflects substantial product variety in the sample.

The structural model analyzes smartphone purchases conditional on owned laptops but does not model the laptop market itself. The IDC data provide laptop brand shares (Table III) but only partially link laptop characteristics to product series and do not provide the product-level price variation, characteristics, and instruments needed to estimate a structural laptop demand and supply system; the cross-sectional survey likewise cannot recover the long-run dynamics of laptop ownership. The analysis therefore takes consumers' laptop holdings as given when modeling smartphone demand, with the implications of this restriction discussed in Section 4.2.

3.3. *Survey*

I survey individuals in the U.S. about their smartphone purchases from 2018 to 2023 and their laptop ownership, following best practices outlined by Allenby, Hardt, and Rossi (2019) and Stantcheva (2023). I survey participants in the experiment and an additional 119 subjects. The survey gathers information on each participant's brand, model/series, and the purchase year of their current and previous smartphones and laptops.[16] Following the literature, I collect series-level data for brands with multiple models (e.g., Eizenberg (2014) utilizes series-level data for personal computers). For instance, in 2022, Samsung released 52 smartphone models across five different series. Since compatibility is typically determined by the series-year rather than the model-year of devices, observing the series and year is sufficient. For current products, the

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[16] If participants are uncertain about their current smartphone information, they are given the option to check the brand, model, and purchase date using their serial number online, e.g., https://iunlocker.com/.

survey also gathers information on participants' second-best choice, which is used to construct a micro-moment.

Since the survey uses a random sample, I reweigh the sample to match the CPS mean and IDC share, as described in Section S.3 of the Supplemental Appendix. The demographic characteristics of the reweighted survey sample are reported in Table S.IV. On average, the reweighted participants are 42 years old, have an annual income of \$52,400, have completed two years of college education, and are 50% female. The most commonly owned laptop brand is HP (30%), followed by Apple (27%).

3.3.1. *Smartphone market definition*

I use the average frequency at which consumers purchase a product to determine the participation probability in each market. To calculate the market size, I divide the U.S. population over 15 years old, as reported by the U.S. Census Bureau (e.g., 273,938,835 in 2022), by the average purchase frequency of the product. The survey indicates that, on average, consumers purchase smartphones every 2.3 years; thus, 43% of the population participates in the smartphone market, resulting in an estimated annual market size of 119 million in 2022. However, because observed IDC sales reach 139 million units, I use this higher figure as the relevant market size. One possible explanation for the discrepancy between the estimated market size and observed sales is that some participants may use more than one device simultaneously, a factor the survey may not fully capture.

I examine the product purchasing timing from the survey to assess whether consumers participate in more than one market simultaneously. Only 1.1% of consumers report purchasing both a smartphone and a laptop in the same transaction. Therefore, I assume that consumers procure a smartphone conditional on already owning a laptop.

I next examine whether smartphone buyers take a future laptop purchase into account. Only 7.1% of participants report considering the cost of a future laptop when purchasing a smartphone. Forward-looking behavior therefore appears rare. I construct a static model in which consumers' decisions depend on current ownership of a complementary good, leaving the small forward-looking minority to future work.

3.3.2. *Evidence for compatibility effects*

Because compatibility varies with the purchase years of the smartphone–laptop pair, the survey provides descriptive evidence on whether consumers are likely to use compatible devices together. The distribution of smartphone purchases conditional on the purchase year of owned laptops (Supplemental Appendix, Figure S.1) shows that most consumers acquire smartphones when their laptops are zero to three years old, suggesting that the two devices are typically owned during overlapping periods in which compatibility features are available.

Survey results on conditional smartphone brand shares align with the experimental findings. Table V, Panel A, reports unconditional smartphone brand shares; Panel B, those conditional on laptop ownership. Apple accounts for 0.50 of smartphone purchases between 2018 and 2023, the highest share in the market. Conditional on owning an Apple laptop, Apple's smartphone share rises to 0.82. Given Apple's closed ecosystem, this increase is consistent with compatibility shaping choices in the market, not only in the experiment.

TABLE VI

Survey results: Alignment between smartphone first and second brand choices

Panel A: Probability that second choice matches first choice		**Panel B: Conditional probability that second choice matches first choice, by laptop brand**				
		Pr(2nd brand choice = 1st brand choice | laptop brand)				
			Smartphone brand			
Smartphone Brand	Pr(2nd brand choice = 1st brand choice)	Laptop Brand	Apple	Samsung	Motorola	Google
Apple	**0.75**	Acer	0.47	0.39	0.08	0.01
Google	0.42	Apple	**0.95**	0.04	0.00	0.00
LG	0.40	Asus	0.41	0.36	0.04	0.01
Motorola	0.23	Dell	0.52	0.40	0.02	0.01
Samsung	0.47	HP	0.53	0.37	0.08	0.00
		Lenovo	0.54	0.23	0.00	0.12
		Microsoft	0.34	0.61	0.00	0.01
		Samsung	0.70	0.30	0.00	0.00

TABLE V

Survey results- smartphone brand shares

Panel A: Smartphone brand share		**Panel B: Smartphone brand share conditional on laptop brand- Top 8 pairs**			
Brand	Share	Smartphone	Laptop	Smartphone-laptop pair share	Smartphone share conditional on laptop brand
Apple	0.50	Apple	Apple	**0.22**	**0.82**
Samsung	0.27	Apple	HP	0.13	0.42
Motorola	0.08	Samsung	HP	0.11	0.38
LG	0.05	Apple	Lenovo	0.07	0.41
Google	0.03	Motorola	HP	0.04	0.13
		Samsung	Asus	0.04	0.54
		Samsung	Lenovo	0.04	0.22
		Samsung	Dell	0.03	0.33

Furthermore, respondents' second smartphone brand choices in the survey provide descriptive evidence on same-brand persistence, one source of which is compatibility. The survey asks: if your current smartphone was unavailable at the time of purchase, what would have been your second choice? Table VI, Panel A, shows that consumers who initially chose Apple or Samsung have probabilities of 0.75 and 0.47, respectively, of selecting the same brand as their second smartphone choice. To relate this persistence to laptop ownership, Table VI, Panel B, provides the probability that the second choice matches the first, by smartphone brand and conditional on laptop brand ownership. Among consumers whose first choice is an Apple smartphone, the probability that the second choice is also Apple is 0.95 for Apple-laptop owners, consistent with Apple's closed ecosystem. The increase relative to the unconditional probability of 0.75 is moderate, since Apple-laptop owners account for a large share of Apple smartphone buyers; the sharper contrast is across laptop brands, with the same figure ranging from 0.34 to 0.70 for non-Apple-laptop owners. These patterns suggest that owned laptops reveal an important source of unobserved preference heterogeneity.

4. MODEL

I employ a random-coefficient discrete choice model that incorporates compatibility with consumers' existing laptops to describe smartphone demand.

4.1. *Demand*

Consumer i makes a discrete choice purchasing smartphone $j \in S$ while owning laptop $c \in C$, maximizing the following indirect utility function:[17]

$$u_{ij} = \sum_{k=1}^{K} x_{jk}\beta_{ik} + q_{jc}\Gamma_i + \lambda_{fj} + \alpha_i p_j + \xi_j + \epsilon_{ij}, \tag{5}$$

where x_{jk} are the standalone characteristics of smartphone j and q_{jc} is the compatibility index between smartphone j and laptop c, defined as the number of available compatibility features, normalized by the maximum number observed in the market that year. For example, independent product characteristics k include screen size, storage, and speed, while q_{jc} aggregates cross-product features such as copy-paste, Camera Continuity, and Handoff.[18] Equation (5) assumes additive separability between x_{jk} and q_{jc}, as the effect of independent smartphone characteristics x_{jk} on utility does not depend on the compatibility index q_{jc}. λ_{fj} represents the brand fixed effect for smartphone j produced by firm f.

A central identification challenge is that compatibility is highly correlated with smartphone-laptop same-brand ownership. Consumers may value choosing a smartphone from the same brand as their owned laptop not only because of compatibility, but also because of familiarity, learning, or other shared brand-specific features. This concern is especially relevant because, in the market data, compatibility is closely aligned with same-brand Apple ownership, making compatibility and brand matching difficult to separate from market variation alone.

The experiment helps address this concern. It measures the change in WTP attributable to compatibility, net of same-brand preferences. Section 5 incorporates this measure through a micro-moment that matches the model-implied expected WTP gain from compatibility to the corresponding experimental WTP gain. This moment disciplines the effect of q_{jc} separately from brand effects conditional on laptop ownership. I also verify that the results are robust to including a brand-matching fixed effect in demand.[19]

Bundling discounts are rare in the smartphone and laptop markets, and consumers usually buy products at different times; therefore, price, p_j, is not individual-specific, whereas consumer i sensitivity to price, α_i, may vary with demographic characteristics. Following Berry, Levinsohn, and Pakes (1999), I assume that a consumer's price sensitivity depends on their income and use a first-order linear approximation for $\log(\text{income}_i - \text{price}_j)$, i.e., $\frac{\text{price}_j}{\text{income}_i}$.

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[17] For simplicity, I omit time index t from the notation.

[18] Fan and Yang (2020) models smartphone demand jointly with carrier contracts because their sample ends in April 2013, when carriers still bundled devices with service contracts; T-Mobile's 2013 "Un-carrier" campaign abandoned service contracts and device subsidies, and other carriers followed. Long-term contract discounts reintroduced in October 2020 do not vary in compatibility and were offered across carriers for the same smartphones, so I examine smartphone demand independently of carrier contracts; Apple's share surge to 50% also predates their reintroduction.

[19] Including a brand-matching fixed effect leaves the compatibility estimate essentially unchanged. Because compatibility and brand matching are highly correlated, however, both coefficients become statistically insignificant. The stability of the compatibility estimate suggests that the experimental WTP micro-moment disciplines compatibility net of brand matching (Section 5.1.1).

ξ_j represents product j's unobservable characteristics, and ϵ_{ij} denotes mean-zero idiosyncratic consumer-product specific terms. β_{ik} and Γ_i are, respectively, individual-specific tastes for independent characteristics k and the compatibility index, as follows:

$$\begin{aligned} \beta_{ik} &= \beta_k + \sum_r d_{ir}\beta^o_{kr} + \beta^u_k \nu_{ik} \\ \Gamma_i &= \Gamma + \sum_r d_{ir}\Gamma^o_r + \Gamma^u \nu_{iq}, \end{aligned} \tag{6}$$

where β_k and Γ are, respectively, individuals' mean taste for independent product characteristics and compatibility. $\boldsymbol{d_i}$ and $\boldsymbol{\nu_i}$ are vectors of observed and unobserved consumer attributes, respectively. Thus, β^o and Γ^o represent individual observed preferences for independent and compatibility product characteristics, respectively, while β^u and Γ^u represent the analogous unobserved tastes. Consumers' attributes include demographics (e.g., income and sex) and ownership of laptops.

Combining Equations (5) and (6) gives

$$\begin{aligned} u_{ij} = \delta_j &+ \sum_{kr} x_{jk} d_{ir}\beta^o_{kr} + \sum_k x_{jk}\nu_{ik}\beta^u_k \\ &+ \sum_r q_{jc} d_{ir}\Gamma^o_r + q_{jc}\nu_{iq}\Gamma^u \\ &+ \alpha_i p_j + \epsilon_{ij}, \end{aligned} \tag{7}$$

where

$$\delta_j = \sum_k x_{jk}\beta_k + q_{jc}\Gamma + \lambda_{fj} + \xi_j. \tag{8}$$

If $q_{jc} = 0$, the compatibility terms vanish and the model reduces to the classic within-market smartphone demand case.

As is customary in the literature (Train, 2009), I normalize the outside good as follows

$$U_{i0} = \epsilon_{i0}.$$

Following the literature, I make specific assumptions about the underlying distributions (Berry, Levinsohn, and Pakes, 1995, Nevo, 2001). I assume a parametric distribution for unobserved heterogeneity, (ν, ϵ), and a non-parametric distribution for observed consumer characteristics, $\boldsymbol{d}$, derived from the reweighted survey data. Additionally, I assume that ξ_j is mean independent of non-price product attributes. To address the simultaneity bias in price, I employ BLP-type instruments along with exchange rates from Japan, South Korea, and China. This allows for the consistent estimation of the parameter vector $\theta = (\delta, \beta^o, \beta^u, \Gamma^o, \Gamma^u)$ using micro-data from the reweighted survey I administer.

Let $\mathbf{D}$ denote the vector of observed attributes $(\mathbf{d}_i)$ and unobserved attributes $(\boldsymbol{\nu}_i, \boldsymbol{\epsilon}_i)$, with its population distribution denoted as $P_{\mathbf{D}}$. The share of consumers selecting product j is obtained by integrating over the attributes of consumers who choose good j. I assume that $(\boldsymbol{\nu}_i, \boldsymbol{\epsilon}_i)$ are distributed independently of $\mathbf{d}_i$ and each other. Specifically, non-price deviations from the mean (ν) are assumed to follow an independent normal distribution, while the unobserved characteristics interacting with price follow a lognormal distribution to avoid a preference for higher prices. In line with standard practice, I assume that the idiosyncratic error, ϵ_{ij}, is independently and identically distributed (i.i.d.) Type-I extreme value (Gandhi and Nevo, 2021). This yields the familiar logit form for the choice probabilities conditional on $(\mathbf{d}_i, \boldsymbol{\nu}_i)$, given in Equation (10). To express the probability compactly, let μ_{ij} collect consumer i's deviations from the mean utility δ_j,

$$\mu_{ij} = \sum_{kr} x_{jk} d_{ir} \beta^o_{kr} + \sum_{k} x_{jk} \nu_{ik} \beta^u_k + \sum_{r} q_{jc} d_{ir} \Gamma^o_r + q_{jc} \nu_{iq} \Gamma^u + \alpha_i p_j. \tag{9}$$

The choice probability conditional on $(\mathbf{d}_i, \boldsymbol{\nu}_i)$ is then

$$Pr_{ij}(\mathbf{d}_i, \boldsymbol{\nu}_i, \boldsymbol{\theta}, \mathbf{x}, \mathbf{q}) = \frac{\exp(\delta_j + \mu_{ij})}{1 + \sum_{l} \exp(\delta_l + \mu_{il})}. \tag{10}$$

4.2. *Supply*

Assume there are F firms in the smartphone market, each producing a subset of the products. Further, as is conventional in the literature (e.g., Berry, Levinsohn, and Pakes, 1995), assume that the marginal cost (*mc*) is independent of the output level and is log-linear in cost characteristics. The *log(mc)* for product j depends on the product's cost shifters, which are assumed to be the same as the product's observed characteristics, x_j, and include exchange rates used as instruments, along with an unobserved ω_j, as follows[20]:

$$log(mc_j) = \gamma x_j + \omega_j. \tag{11}$$

Marginal cost mc_j is independent of compatibility and of the consumer's laptop type. Prices, in contrast, are uniform across consumers within a given smartphone j — firms do not condition p_j on the buyer's laptop ownership — but the equilibrium level of p_j depends on the distribution of laptop ownership in the market through its effect on aggregate demand. A larger mass of consumers tied to smartphone j through compatibility raises the markup the firm can sustain. Firm $f \in F$ chooses prices to maximize expected profit across laptop types:

$$\max_{p_j} \pi^f = \sum_{c \in C} P(c) \sum_{j \in S^f} \left[p_j - mc_j\right] s_j(p \mid c) \times M, \tag{12}$$

where S^f is the set of smartphones produced by firm f, $P(c)$ is the population share of consumers owning laptop c, $s_j(p \mid c)$ is the market share of smartphone j among consumers owning laptop c, and M is the size of the smartphone market, as described in Section 3.3.1. The conditional representation makes explicit that firms internalize the composition of laptop owners in the market when setting prices. Because p_j does not vary with laptop c, the first-order conditions reduce to the standard Bertrand–Nash form in aggregate demand, $s_j(p) + (p_j - mc_j), \partial s_j(p)/\partial p_j = 0$, where $s_j(p) = \sum_c P(c), s_j(p \mid c)$; Section S.5 of the Supplemental Appendix establishes this equivalence formally. The aggregate elasticity already averages over $P(c)$, so part of the observed price is a compatibility-driven markup reflecting the composition of laptop ownership.

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[20] The implicit assumption is that the marginal cost is independent of compatibility. For firms that design their software or compatibility features (e.g., Apple), the marginal cost of software is practically zero (Arora, Caulkins, and Telang, 2006, Ellison and Fudenberg, 2000). This assumption also holds for manufacturers relying on external software. Even if software providers were included in the model, smartphone and laptop firms either use open-source software (e.g., Android) or bundle the cost within the product price (e.g., Windows license).

The laptop ownership distribution $P(c)$ is predetermined within the smartphone purchase period, though it may partly reflect earlier smartphone choices. I treat it as fixed within each estimation year and estimate the model against the contemporaneous $P(c)$. Only 1.1% of consumers buy a smartphone and laptop together (Section 3.3.1), so feedback from current prices to current ownership is negligible, and conditioning on the contemporaneous ownership distribution is standard differentiated-products practice (Goldberg, 1995, Petrin, 2002, Berry, Levinsohn, and Pakes, 2004). The counterfactuals therefore hold $P(c)$ fixed and evaluate welfare on the current pool of buyers conditional on realized laptop holdings, leaving the long-run adjustment of ownership distributions—which the present data cannot identify—to future work. Perturbing any laptop brand's ownership share by 5% in either direction moves the consumer-surplus gain by less than 1% (Section S.6 of the Supplemental Appendix).

4.3. *Economic Forces Under Open Ecosystems*

Open ecosystems allow consumers to combine smartphones and laptops from different brands while maintaining cross-product compatibility. Under closed ecosystems, an owned laptop c may be compatible with smartphone j but not with smartphone $\tilde{j}$, i.e., $q_{jc} > 0$ and $q_{\tilde{j}c} = 0$. Under open ecosystems, smartphone $\tilde{j}$ and laptop c become potentially compatible. I model this by allowing consumers to use the highest compatibility level available from either side of the smartphone–laptop pair:

$$q_{\tilde{j}c} = \max\{q_{\tilde{j}\cdot}, q_{\cdot c}\},$$

where, with abuse of notation, $(\cdot)$ denotes any other compatible smartphone or laptop.

I use this maximum-compatibility rule as the main open-ecosystems specification and also report results under an alternative minimum-compatibility rule, $q_{\tilde{j}c} = \min\{q_{\tilde{j}\cdot}, q_{\cdot c}\}$, under which compatibility is constrained by the weaker side of the smartphone–laptop pair (Section 6.1.1). The maximum rule represents a strong interoperability policy.[21] The minimum rule captures a weaker policy that guarantees only baseline cross-device functionality and generates weaker switching incentives. These two cases bound the policy environment considered in the counterfactual analysis.

This policy changes the source of compatibility value. Under closed ecosystems, compatibility creates a business-stealing effect: for example, Apple laptop owners must purchase an Apple smartphone to obtain Apple-level compatibility. Under open ecosystems, compatibility becomes a spillover from the owned laptop to competing smartphones. An Apple laptop owner who purchases a Samsung smartphone can still benefit from Apple-level compatibility. As a result, open ecosystems reduce switching costs and increase substitutability across smartphones, generating a competitive displacement effect in the smartphone market.

The welfare effects are ambiguous. Open ecosystems may expand smartphone demand by letting consumers obtain compatibility without a matched pair; if this expansion outweighs the increase in competitive pressure, prices may rise and reduce surplus for consumers with low compatibility valuation Γ_i or high price sensitivity α_i. They may also reallocate demand asymmetrically: a firm with both high compatibility and superior independent characteristics x_{jk} can attract consumers from other ecosystems—for example, non-Apple laptop owners switching to Apple smartphones when Apple offers stronger hardware—raising concentration.

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[21] Article 6(7) of the Digital Markets Act requires gatekeepers to allow effective interoperability with hardware and software features controlled through designated operating systems or virtual assistants. The European Commission has applied this provision to Apple's interoperability with third-party devices and services.

5. ESTIMATION AND RESULTS

I estimate the model by GMM with the `pyblp` package (Conlon and Gortmaker, 2020, 2023). The demand and marginal-cost estimations mostly follow Berry, Levinsohn, and Pakes (2004), with the key distinction that the model adds ownership-survey and experimental micro-moments to discipline substitution patterns and the value of compatibility. Identification of the compatibility coefficient, Γ, comes from variation in compatibility across consumers who own different laptops for a given smartphone, with the experimental moment providing direct variation in WTP for compatibility.

The first micro-moment comes from the ownership survey and disciplines substitution patterns across smartphone brands. Following Berry, Levinsohn, and Pakes (2004), Grieco, Murry, and Yurukoglu (2024), and Grieco, Murry, Pinkse, and Sagl (2025), I use second-choice data, which is informative about the correlation in consumer tastes that aggregate shares alone cannot recover. Specifically, I match the share of consumers whose first and second smartphone choices are both Apple, capturing whether a consumer who most prefers an Apple smartphone turns to another Apple smartphone, rather than to a rival, as the next-best alternative.[22]

The second moment comes from the experiment and disciplines the compatibility coefficient Γ. Let $\widehat{WTP}_i$ be the experimentally measured WTP gain from compatibility for consumer i, net of same-brand preferences, and let $c(i)$ be i's owned laptop. Define $\kappa_{ij} = \mathbf{1}\{q_{jc(i)} > 0\}$ and $\rho_i(\theta) = \sum_j s_{ij}(\theta)\,\kappa_{ij}$, the model-implied probability that i purchases a compatible smartphone. Among consumers for whom $\widehat{WTP}_i$ is observed, the moment matches the mean experimental WTP of compatible buyers to its model analog:

$$\underbrace{\frac{\mathbb{E}_{P_{\mathbf{D}}}\left[\widehat{WTP}_i\,\rho_i(\theta)\right]}{\mathbb{E}_{P_{\mathbf{D}}}[\rho_i(\theta)]}}_{\text{model}} = \underbrace{\frac{\mathbb{E}_e\left[\widehat{WTP}_i\,\kappa_{i,j(i)}\right]}{\mathbb{E}_e[\kappa_{i,j(i)}]}}_{\text{data}}, \tag{13}$$

where $j(i)$ is i's realized choice. The data side averages $\widehat{WTP}_i$ over realized compatible buyers; the model side replaces realized purchases with the choice probabilities $\rho_i(\theta)$, which depend on Γ through $s_{ij}(\theta)$. Matching the two means therefore identifies Γ. For interpretation, I convert the estimated Γ to a per-feature dollar value by dividing by the income-weighted marginal utility of income, $|\bar{\alpha}|$, which yields \$29.

A final identification concern involves firm conduct. Observed prices reflect both consumer demand and firms' markup-setting behavior. Because demand and supply are estimated jointly, the Bertrand–Nash pricing equations enter the common GMM objective and, strictly speaking, bear on every estimate, including Γ. The experimental micro-moment limits this influence. Because WTP is elicited at prices set by random draw rather than by firm optimization (Section 2.2), it provides variation in compatibility valuation that is less tied to firms' equilibrium pricing decisions. The conduct assumption therefore matters mainly for the cost side: if observed prices partly reflect dynamic incentives, such as pricing aimed at future ecosystem participation or future lock-in, the recovered marginal costs may absorb part of these dynamic markup components. This affects the markup–cost decomposition rather than the compatibility channel.[23]

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[22] I also considered a second-choice moment conditioned on laptop ownership; Section 5.1.1 explains why it is not used.

[23] The counterfactuals in Section 6 evaluate how equilibrium prices respond to changes in compatibility structure, which is governed by Γ and the curvature of demand rather than the level of marginal cost. The counterfactual price differences are therefore robust to moderate departures from static best-response pricing.

5.1. *Results*

Table VII presents the demand and marginal cost estimation results.[24] The results show that consumers value smartphones' dependent and independent characteristics, which is consistent with the experimental outcomes. Consumers value one additional smartphone compatibility characteristic with laptops at \$29, which is the estimated weighted average WTP in the experiment.

Consumers value an additional 0.1-inch increase in screen size at \$17.6, a 0.1 GHz increase in processor speed at \$20.9, and an additional 10 GB of storage at \$9.3. The megapixel estimate is statistically insignificant, consistent with smartphone photography shifting from a hardware-first "megapixel race" toward software-driven image quality.[25] Apple's fixed effect is the highest at \$277, followed by Samsung's at \$155. The Apple fixed effect is lower than the comparable estimate in Fan and Yang (2020), reflecting that compatibility absorbs part of what would otherwise be captured by brand fixed effects. The random coefficient on potential compatibility is positive but statistically insignificant. This suggests that substitution patterns are driven primarily by observed product characteristics, brand fixed effects, income heterogeneity, and the mean compatibility channel induced by consumers' laptop ownership, rather than by additional unobserved heterogeneity in compatibility tastes.

Own-price elasticities for the top smartphones are negative and large, implying that a one-percent price increase reduces a product's demand by 2.4–6.7 percent, while cross-price elasticities are positive and smaller, with closer competitors more responsive (Supplemental Appendix, Table S.VI). Most cross-brand elasticities are substantially lower than those in Fan and Yang (2020), reflecting the compatibility effect that ties consumers to ecosystems. The aggregate diversion ratios (Supplemental Appendix, Table S.VII) further show that, because smartphones are near-essential, displaced consumers overwhelmingly substitute to other smartphones rather than to the outside good.

These aggregate ratios, however, mask the channel through which compatibility shapes substitution. To isolate it, Table VIII reports diversion from the 2018 iPhone X separately for consumers who own an Apple laptop and those who do not. Among Apple-laptop owners, 87.5% of diverted demand stays within the Apple smartphone lineup and only 8.0% goes to Samsung. Among non-Apple-laptop owners, by contrast, 29.9% of diverted demand goes to Samsung, nearly four times the share among Apple-laptop owners, while 59.1% stays within Apple. Outside-good diversion is negligible for both groups. This exercise illustrates how the estimated model captures compatibility lock-in: consumers who own Apple laptops are substantially less willing to switch across ecosystems in response to a price increase, even though their own-price elasticities are similar to those of non-Apple-laptop owners. This substitution-pattern asymmetry is the demand-side mechanism underlying the open-ecosystems counterfactual in Section 6.

Figure 2 depicts smartphones' average normalized hardware quality (i.e., x_j in Equation (5)) between 2018 and 2023. The quality index is a composite measure derived from the hardware characteristics, weighted by their estimated coefficients. Apple's average hardware quality is the highest, with Samsung as its closest competitor. In 2018 and 2019, there is a large gap in the average hardware quality between Apple and Samsung, but this gap shrinks starting in 2020 and remains low, with some Samsung smartphones surpassing Apple's. This change in the average quality gap may play an important role when compatibility changes.

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[24] For 29 low-priced products among the 636, the implied marginal cost is negative; these are excluded from the marginal-cost estimation.

[25] See Delbracio, Kelly, Brown, and Milanfar (2021), which surveys how advances in computational photography shifted smartphone imaging from hardware-centric image capture toward software-driven processing.

TABLE VII

SMARTPHONE ESTIMATION RESULTS

Variable	Parameter	Standard error
Individual level coefficient		
Price/income	-65.3642	26.8015
Compatibility	2.9110	1.2953
Common coefficient		
Screen size (inches)	1.9428	0.2866
Storage (GB)	0.0103	0.0023
Processor speed (GHz)	2.3083	0.4970
Megapixels	0.0028	0.0038
Apple	3.0502	0.4353
Samsung	1.7103	0.2313
LG	0.1048	0.2461
Absorb Year FE	Yes	
Random coefficient		
Compatibility product	0.0733	3.0329
Marginal cost ($)		
Screen size (+0.1 inch)	339.88	12.65
Megapixels (+1 MP)	317.37	1.70
Storage (+1 GB)	312.68	0.51
Processor speed (+0.1 GHz)	413.24	21.68
Absorb Year FE	Yes	

Note: “Compatibility product" is a device’s binary potential compatibility index. Marginal-cost entries report the implied marginal cost in dollars, averaged across products, for the indicated increase in each characteristic relative to baseline. Baseline average MC is $310.40.

TABLE VIII

CONDITIONAL DIVERSION FROM THE 2018 IPHONE X BY LAPTOP OWNERSHIP

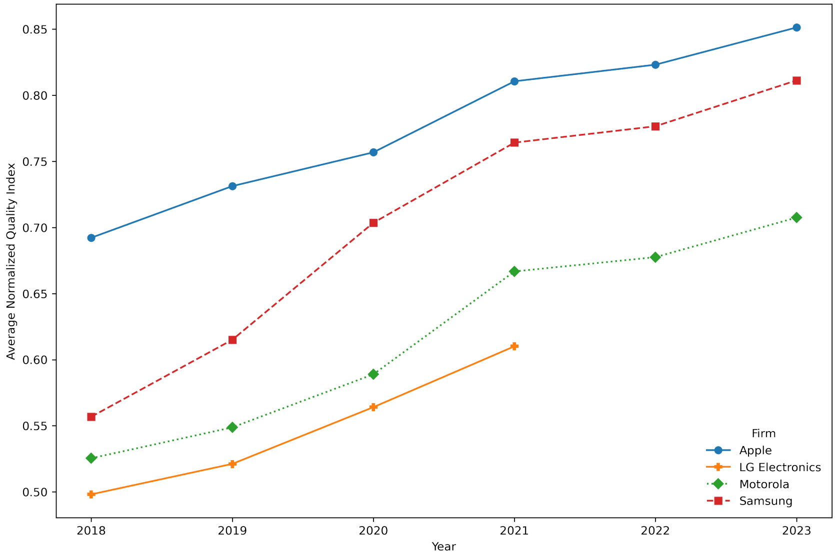
Destination	Apple-laptop owners	Non-Apple-laptop owners	Difference
Other Apple smartphones	0.8754	0.5910	−0.2843
Samsung smartphones	0.0803	0.2997	+0.2194
Other smartphones	0.0431	0.1064	+0.0632
Outside good	0.0012	0.0030	+0.0017

Note: Each column reports the diversion ratio from the 2018 iPhone X, computed separately for Apple- and non-Apple-laptop owners. Entries are the share of demand lost from the iPhone X following an infinitesimal price increase that is reallocated to each destination category. “Difference” is the non-Apple column minus the Apple column. This conditional decomposition is not a targeted moment in the GMM estimation.

5.1.1. *Model fit*

The GMM procedure targets two micro-moments: the probability of choosing an Apple smartphone as both first and second choice, and the experimentally measured WTP gain from compatibility, $\widehat{WTP}$, evaluated on consumers who own an Apple smartphone and an Apple laptop. The first column of Table IX reports the data, while the second column presents the corresponding model-implied moments. The model closely replicates both the Apple second-choice moment and $\widehat{WTP}$, indicating a strong overall fit.

FIGURE 2.—Smartphone average hardware quality by year



Note: The figure shows the evolution of smartphone hardware quality (x_k in Equation 5) over time. For each year, I calculate hardware quality using smartphone characteristics weighted by the estimated utility parameters. LG exited the smartphone market in 2021.

The alternative specifications are diagnostic: each micro-moment disciplines a distinct object. Dropping the substitution moment (Column 3) improves the fit of the experimental WTP moment slightly but worsens the Apple first and second choice fit. Dropping the experimental moment (Column 4) leaves the substitution fit essentially unchanged and changes $\widehat{WTP}$ only modestly: compatibility still enters utility, but the magnitude of the compatibility effect is informed only indirectly by substitution patterns rather than by direct experimental variation in WTP. Dropping both micro-moments (Column 5) degrades both targets; in particular, $\widehat{WTP}$ falls to 90.68, further from the experimental value than under any specification that retains a micro-moment. Thus, the substitution moment disciplines survey substitution patterns, while the experimental moment disciplines the magnitude of the compatibility effect.

TABLE IX

MODEL FIT - KEY MEASURES

			Alternative Specifications		
	Data	Model	Only WTP moment	Only Apple 1st&2nd choice moment	No micro moments
E[WTP | compatibility]	96.3574	94.1339	95.2005	92.4432	90.6799
Apple 1st & 2nd choice	0.3796	0.3729	0.3446	0.3733	0.3623

Note: The Data column reports the empirical target for each micro moment; all other columns report the corresponding model-implied value for that specification.

The specification includes an Apple fixed effect but no Apple random coefficient. An Apple random coefficient would ordinarily be identified by second-choice data. In this market, however, the compatibility coefficient predicts the same second-choice pattern: consumers who own a connected device—predominantly an Apple laptop—value compatibility and thus select Apple smartphones as both their first and second choices. This is precisely the pattern the Apple first-and-second-choice moment measures, so unconditional second-choice moments are informative about both coefficients but cannot identify them separately. The brand random coefficient could in principle be identified by adding second-choice moments conditioned on Apple-laptop ownership: compatibility implies within-Apple substitution increasing in ownership, whereas a taste draw independent of predetermined holdings implies substitution invariant to ownership. Targeting such moments, however, would reintroduce the confounding of brand matching with compatibility, since ownership is selected on brand tastes, and would contaminate precisely what the experiment identifies: willingness to pay for compatibility net of brand matching. I therefore leave heterogeneous brand taste unparameterized and anchor the compatibility coefficient to the experimental $\widehat{WTP}$ moment, while the unconditional Apple first-and-second-choice moment disciplines substitution patterns.

6. COUNTERFACTUAL

This section uses the estimated parameters to conduct counterfactual simulations for open ecosystems and the cross-market merger between Samsung and HP, Apple's main competitors. These analyses demonstrate the significance of cross-product compatibility in determining welfare outcomes.

6.1. *Open-ecosystems welfare effect*

Under open ecosystems, consumers can obtain cross-ecosystem compatibility. Applying the maximum-compatibility rule from Section 4.3, I solve for equilibrium smartphone prices and market shares and calculate consumer and producer surplus.

Table X shows the average effect of open ecosystems across firms for each year from 2018 to 2023. The results reveal that, on average, the inside-good share increases by 4.15 percentage points, prices decrease by \$25.37, and consumer surplus rises by \$11.46 billion. For scale, average annual U.S. smartphone revenue in the sample is roughly \$98 billion, so the consumer-surplus gain amounts to 11.7% of annual market revenue. Open ecosystems increase product substitutability by allowing consumers to obtain compatibility benefits across brands, which generally strengthens competition and lowers prices. However, the gains are not uniform across consumers: when prices increase, consumers with low compatibility values may be worse off because they benefit little from expanded compatibility but still face higher prices. The profit effect varies across years and is negative on average, as Apple's losses outweigh competitors' gains. This reflects Apple's cross-market power in closed ecosystems, where its laptop owners are tied to Apple smartphones for compatibility. In open ecosystems, this tie is broken: Apple laptop owners obtain similar compatibility from either smartphone brand, eroding Apple's captive demand.

Table XI presents the annual average impact of open ecosystems on firms. Apple's profit declines while competitors' profits rise, consistent with greater smartphone substitutability once compatibility no longer ties consumers to ecosystems. Apple's average price reduction is about five times greater than that of its competitors, with a mean decrease of \$60.66. Despite this significant price drop, Apple's contribution to the increase in consumer surplus remains the lowest, driven by low price elasticity and varying substitution patterns across periods. To illustrate these patterns, I examine changes in firms' annual profits and prices.

Figure 3 illustrates the annual changes in firms' profits under open ecosystems. Apple's profits increase in 2018 and 2019, but decline sharply from 2020 onward. The largest Apple profit

TABLE X

OPEN ECOSYSTEMS: AVERAGE EFFECT ACROSS FIRMS

Market	ΔInside good share	ΔSmartphone price	ΔFirms profit	ΔCS
2018	0.0177	-20.03	-17.60	10,733.78
2019	0.0312	-3.82	326.42	9,207.87
2020	0.0350	-40.75	-2,146.16	11,477.37
2021	0.0332	-23.11	-492.42	10,964.79
2022	0.0553	-26.71	-492.02	13,260.75
2023	0.0764	-37.77	-59.32	13,144.27

Note: CS refers to consumer surplus. Both profit and CS are reported in millions.

TABLE XI

OPEN ECOSYSTEMS: AVERAGE FIRM EFFECT ACROSS YEARS

Firm	ΔInside good share	ΔSmartphone price	ΔFirms profit	ΔCS
Apple	0.0125	-60.66	-2,648.55	1,969.11
LG	0.0371	-14.65	333.41	5,210.66
Motorola	0.0627	-8.71	788.96	4,805.86
Samsung	0.0440	-11.58	-191.51	6,057.69

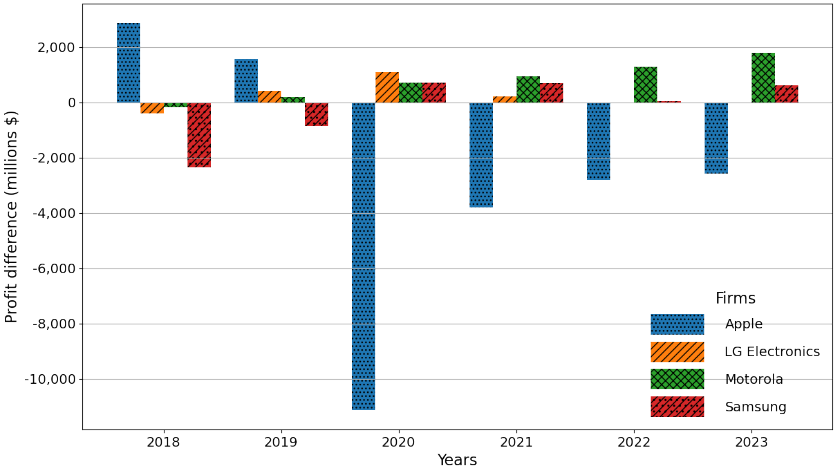
Note: CS refers to consumer surplus. Both profit and CS are reported in millions.

loss occurs in 2020, after which the losses decrease monotonically from 2021 to 2023. Samsung follows the opposite pattern: it loses profits when Apple gains and gains profits when Apple loses. The two smaller firms, LG and Motorola, exhibit more heterogeneous effects. These patterns suggest that open ecosystems weaken Apple's cross-market advantage by increasing substitutability between Apple and non-Apple smartphones for Apple laptop owners. As consumers are less tied to Apple for compatibility, Apple reduces prices and loses profits, while Samsung captures some of the displaced demand. The declining magnitude of Apple's losses after 2020 is consistent with changing substitution patterns across years.

The timing of these reversals tracks the Apple–Samsung hardware-quality gap in Figure 2. In 2018–2019, Apple's hardware-quality advantage is substantial. Consumers previously tied to Samsung's ecosystem therefore switch to Apple to gain both compatibility and hardware quality, raising Apple's profit and market concentration. From 2020 onward, this advantage narrows, and some Samsung devices surpass Apple's. Apple-laptop owners then switch to Samsung without sacrificing compatibility. This produces a profit loss for Apple, gains for its competitors, and a fall in market concentration.

Apple's profit loss from the open-ecosystem counterfactual declines from $11.1 billion in 2020 to $2.5 billion in 2023, with most of the decline occurring between 2020 and 2021. Apple-laptop owners' incentive to switch to Samsung depends on the Apple–Samsung quality gap in the percentile range to which they would migrate, and weakens as Apple's position improves. From 2020 to 2022, the gap widens in Apple's favor through the upper-middle and upper percentiles, where Samsung had led in 2020, shrinking the switch-prone population. In 2023 the pattern is mixed: relative to 2022, Apple widens its positive lead across the middle of the distribution and narrows Samsung's lead at the top two percentiles, while its gap falls across the 61st to 96th. Even in that range, however, Apple's position remains improved relative

FIGURE 3.—Open ecosystems effect on firms profit by year



to 2020, so the switching incentive remains weaker than in 2020 and the now-small profit loss continues to shrink (Supplemental Appendix, Figure S.2).

6.1.1. *Minimum compatibility*

I examine the welfare effects of a regulator mandating open ecosystems while forcing only *minimum* compatibility between any smartphone-laptop pair, defined as $q_{\tilde{j}c} = \min\{q_{\tilde{j}\cdot}, q_{\cdot c}\}$. This contrasts with the policy analyzed above, where the regulator enforces *maximum* compatibility.

Under *minimum* open ecosystems, Apple's profit, price, and inside-good share rise on average—by $4.6 billion, $21.15, and 0.047, respectively—while competitors' outcomes fall. Samsung experiences the largest competitor decline, with profit, price, and inside-good share falling by $1 billion, $16.07, and 0.017, respectively. Consumer surplus nevertheless increases, as it does under maximum compatibility (Supplemental Appendix, Table S.VIII).

The intuition follows from switching incentives under the two regimes. Under *maximum* compatibility, from 2020 to 2023 Apple loses share and profit because its laptop owners can switch to higher-quality Samsung smartphones without sacrificing compatibility; under *minimum* compatibility, switching entails a compatibility loss, so Apple laptop owners are less likely to switch. In 2018–2019, switching to Apple under the minimum rule leaves non-Apple laptop owners' compatibility unchanged, so their switching decisions are driven solely by Apple's higher hardware quality.

The results show that while open ecosystem regulation increases welfare both with maximum and minimum compatibility, the implications for market concentration vary substantially. Allowing for *minimum* compatibility allows Apple to increase its prices and reinforce its market power. In contrast, the effect of open ecosystem regulation that requires *maximum* compatibility varies depending on smartphone quality.

6.1.2. *Compatibility license*

Regulators have also required firms to license products and patents so that consumers can benefit from licensed features when purchasing competitors' products.[26]

Licensing Apple's compatibility allows consumers to connect smartphones to any laptop at Apple's compatibility level without owning any Apple product. This differs from open ecosystems, where consumers need at least one Apple product to obtain Apple's compatibility level. When Apple licenses compatibility to Samsung alone or to all competitors, Apple's profit decreases by more than its competitors' profits increase. The reason is that Apple initially has near-monopolistic power over consumers who benefit from its compatibility. Consequently, no simple fixed-fee contract exists under which Apple agrees to license its compatibility.

6.2. *Cross-market merger*

Existing antitrust policies scrutinize cross-market mergers of technology firms without considering the causal effect of compatibility on demand (e.g., the DOJ's 2014 report on Lenovo's acquisition of Motorola), and may therefore fail to address their impact.

I examine the effect of a cross-market merger between Samsung, which holds only a 3% share of the laptop market, and HP, which holds the largest share. Following the merger, the Samsung–HP entity provides maximum compatibility between Samsung smartphones and laptops produced by Samsung or HP—comparable to that within Apple's ecosystem—and chooses how much compatibility to extend to rival non-Apple laptops. I find that, rather than foreclosing these rivals, the profit-maximizing policy keeps their compatibility positive, as before the merger. This lower compatibility keeps Samsung smartphones attractive to rival non-Apple laptop owners, since they receive more compatibility than they would from Apple smartphones. I evaluate the merger under this endogenous compatibility choice, solve for the resulting equilibrium prices and market shares, and calculate consumer and producer surplus.

Across years, the Samsung–HP merger modestly raises inside-good shares and reduces Apple's share, with the largest effects before 2021 (Supplemental Appendix, Table S.IX). Average smartphone prices and aggregate firm profits increase in the first three years, when Samsung's pre-merger compatibility is less common and the merger therefore generates a larger compatibility gain for the merged firm. In later years, as Samsung compatibility becomes more widespread and the hardware-quality gap changes, these market-level price and profit effects weaken and eventually turn negative. Despite price increases in some years, the average effect on consumer surplus remains positive.

Table XII provides the effect of the Samsung-HP merger on firms across years. On average, Samsung's market share increases by 11.12% while Apple's decreases by 7.66%, leading to a lower market concentration. The increase in Samsung's share at Apple's expense comes from HP laptop owners who previously preferred Apple over Samsung's low compatibility. Samsung's prices rise by $142.19 and its profit by $9.3 billion, while its competitors' prices and profits decline. This price increase has a heterogeneous effect on consumer surplus, making those with low compatibility value worse off. Although a decrease in market concentration usually accompanies lower prices, Samsung's prices increase due to its cross-market power, which ties consumers to its ecosystem for compatibility benefits.

Note that if Samsung's prices increase and Apple's prices do not decrease, regulators may block the merger. Such a scenario may occur if, prior to the merger, consumers who own HP

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[26] For example, in the Qualcomm litigation, the 2020 Ninth Circuit decision discusses commitments to license standard-essential patents on fair, reasonable, and nondiscriminatory (FRAND) terms; see https://cdn.ca9.uscourts.gov/datastore/opinions/2020/08/11/19-16122.pdf.

TABLE XII

SAMSUNG-HP MERGER: AVERAGE FIRM EFFECT ACROSS YEARS

Firm	ΔInside good share	ΔSmartphone Price	ΔFirms profit	ΔCS
Apple	-0.0766	-42.29	-6,669.35	335.84
LG	-0.0084	-0.92	-192.41	1,279.13
Motorola	-0.0093	-1.98	-209.15	1,110.69
Samsung	0.1112	142.19	9,305.28	909.39

Note: CS refers to consumer surplus. Profit and CS are in millions.

laptops and purchase Apple smartphones place zero value on compatibility. In this case, the merger does not negatively impact Apple's prices, allowing Samsung to increase its prices further, potentially resulting in a negative effect on consumer surplus.

To conclude, the Samsung–HP cross-market merger increases average consumer surplus and reduces smartphone market concentration, though consumers with low compatibility value may be worse off; others benefit from lower prices or enhanced Samsung–HP compatibility. Regulators should therefore consider approving the merger while accounting for the merged entity's compatibility incentives toward rival non-Apple laptop producers. More broadly, antitrust analysis of cross-market mergers should account for compatibility as a channel through which firms can affect demand, prices, and market concentration.

7. CONCLUSION

Antitrust scrutiny of technology ecosystems often focuses on a primary good and its add-ons. This paper instead studies two standalone products, smartphones and laptops, that are useful independently but whose compatibility shapes demand and competition. Using an incentivized experiment, I show that compatibility has a causal effect on smartphone demand. I then use this experimental evidence to discipline a structural model of smartphone demand conditional on laptop ownership. The estimates show that compatibility is an important source of demand and that its competitive effects depend on both ecosystem structure and the hardware-quality gap across firms.

The counterfactuals deliver two main findings. First, mandating open ecosystems raises consumer surplus, but whether it raises or lowers smartphone-market concentration depends on the Apple–Samsung hardware-quality gap. Second, cross-market mergers can reshape competition even when the merging firms are not close rivals within the same product market. In a counterfactual Samsung–HP merger, expanded compatibility strengthens Samsung against Apple and reduces smartphone-market concentration, but also raises Samsung prices and can leave consumers who value compatibility least worse off.

The analysis is static and holds product characteristics fixed, leaving dynamic responses in design and investment to future work. The finding that open-ecosystem effects hinge on the quality gap suggests that interoperability may shift innovation away from closed-ecosystem features and toward hardware quality or compatibility features that remain valuable under interoperability. More broadly, compatibility between standalone products is an economically important channel of cross-market power. Antitrust analysis of technology ecosystems should therefore account not only for substitution within markets, but also for how compatibility links demand across independently purchased products.

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S.1. EXPERIMENTAL PROCEDURES AND AUXILIARY RESULTS

Participants face decision-dependent incentives that are large relative to a recent Prolific benchmark, and these incentives are straightforward to compute. The probability of winning the lottery is 0.001. Participants face at most eight WTP questions contingent on the lottery payment, while a small group observes only four WTP questions, all with compatibility information. Prize values range from $1,799 to $2,597. The expected value of the WTP questions is therefore $1.76–$2.96, or $0.22–$0.37 per question, on top of the participation fee. As a benchmark, these incentives exceed the decision-dependent component in Exley and Nielsen (2024), which pairs a comparable $12 average hourly participation fee with a decision-dependent bonus of $0–$1.[1]

Participants complete comprehension questions verifying that they understand the payoff consequences of reporting a WTP below or above the randomly drawn price, p. On average, participants spend 3.3 minutes on these questions.

Before the WTP elicitation, participants are asked whether they are eligible for discounts when purchasing devices, such as Apple's student discount for computers. This helps explain WTP variation due to retail price differences. To reduce concerns about switching costs, including moving across ecosystems, participants are also informed that professional support is provided to transfer their data to their new devices and learn about their functionalities.

The larger absolute difference-in-difference in WTP for Apple smartphones in Table II, Panel B, of the main text partly reflects auxiliary selection. Apple product owners have higher-than-average valuations for Apple products, consistent with a brand endowment effect. In addition, Apple offers more connectivity features than Samsung. Although the experiment provides the same compatibility information for Apple and Samsung products, Apple owners may have greater familiarity with additional Apple connectivity features, raising the average Apple WTP difference.

S.2. WTP

Tables S.I and S.II report the gender difference in WTP without and with compatibility information, respectively (the former also by pre-knowledge state). This gender difference may reflect the relationship between choice experiments and personality traits documented by Grebitus, Lusk, and Nayga Jr (2013). Table S.III reports the anchoring robustness check discussed in Section 2.5.1 of the main text.

TABLE S.I

WTP: STATE-GENDER, NO INFO

Brand	Knowledge status	Gender	N	Mean WTP compatibility	Mean WTP incompatibility	Mean difference
Apple	✗	Male	146	423.22 (232.64)	415.06 (235.55)	8.16
Samsung	✗	Male	191	428.82 (226.14)	426.93 (231.06)	1.88
Apple	✗	Female	113	410.89 (249.29)	401.25 (250.22)	9.65
Samsung	✗	Female	166	359.95 (244.79)	349.04 (247.31)	10.91
Apple	✓	Male	379	500.49 (223.53)	485.29 (223.08)	15.20***
Samsung	✓	Male	334	496.57 (210.03)	478.71 (210.20)	17.86***
Apple	✓	Female	246	514.32 (228.26)	492.45 (233.45)	21.87***
Samsung	✓	Female	193	478.46 (222.37)	459.23 (233.69)	19.23**

TABLE S.II

WTP: GENDER, INFO

Brand	Information	Gender	N	Mean WTP compatibility	Mean WTP incompatibility	Mean difference
Apple	✓	Male	588	495.74 (225.28)	410.02 (214.55)	85.73***
Samsung	✓	Male	588	481.07 (216.18)	407.48 (210.99)	73.59***
Apple	✓	Female	394	497.93 (229.36)	386.72 (231.44)	111.22***
Samsung	✓	Female	394	440.13 (232.94)	352.30 (237.71)	87.83***

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[1] I use Exley and Nielsen (2024) as a benchmark because it was conducted around the same time and therefore provides a recent reference point for incentive payments on Prolific.

TABLE S.IV

REWEIGHTED DEMOGRAPHIC AND OWNED LAPTOP

	Panel A: Demographic			**Panel B: Owned laptop**			
	Initial	Reweight	CPS	Brand	Initial	Reweight	IDC
Age	39.94 (10.26)	42.34 (13.59)	43.44 (13.42)	HP	0.1966	0.30	0.31
Income	\$59,837.80 (42,540.92)	\$52,409.33 (44,178.67)	\$52,945.03 (44,241.33)	Apple	0.1791	0.27	0.27
Education	15.01 (2.20)	14.05 (2.44)	14.03 (2.46)	Lenovo	0.1215	0.16	0.17
Gender	1.44 (0.51)	1.50 (0.50)	1.52 (0.50)	Dell	0.1867	0.10	0.10
				Acer	0.0641	0.08	0.08
				Asus	0.0817	0.07	0.07

TABLE S.III

WTP CONDITION ON INFORMATION GROUP

Smartphone brand	Information group	N	Mean WTP compatibility	Mean WTP incompatibility	Mean difference
Apple	✗, ✓	893	494.79 (228.87)	398.33 (222.49)	96.46***
Samsung	✗, ✓	893	464.77 (226.03)	384.4681 (222.79)	80.31***
Apple	✓	99	496.81 (223.09)	400.48 (223.29)	96.33***
Samsung	✓	99	450.43 (217.97)	376.80 (240.14)	73.62***

Note: Information group ✗, ✓ indicate that participants first report on WTP without compatibility information and then with, while group ✓ receive the information immediately. Standard deviations are in parentheses. Statistical significance is denoted as: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

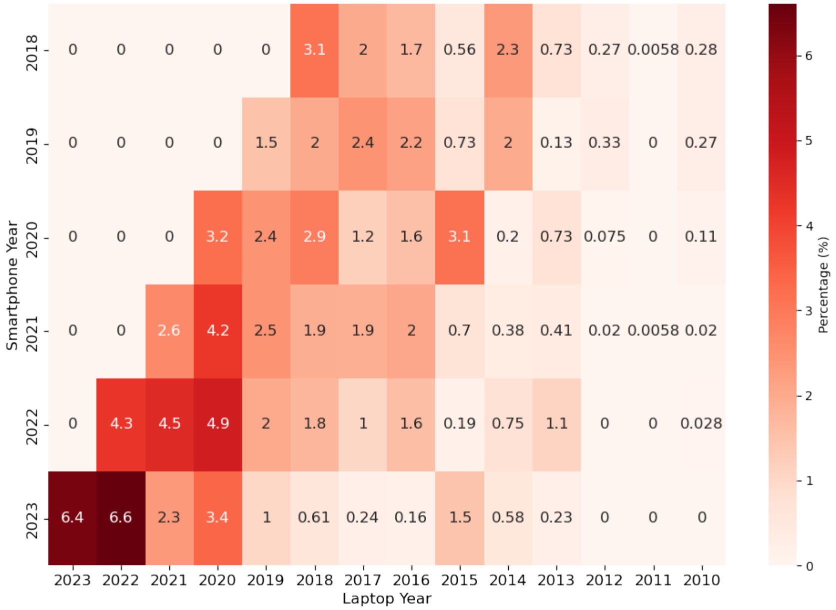
S.3. REWEIGHTING SURVEY DATA

The IDC repeated cross-section data is representative of the U.S. smartphone and laptop markets. Since the current study connects the cross-section data by surveying product ownership across multiple markets, it is essential that the survey is representative of the U.S. population. Therefore, the paper reweights the survey data for age, income, education, and sex to match the 2023 Current Population Survey (CPS) averages and adjusts product ownership to align with the 2018-2023 average shares from IDC.

Reweighting the survey is done iteratively by updating the weights of observations based on their characteristics relative to the CPS distribution and IDC, known as the random iterative method (RIM). In each iteration, the procedure updates the weights based on the ratio of the probability of observing a particular demographic category in the representative data to the probability of observing the same demographic category in the survey, i.e., $\frac{Pr(demographic_k^{representative})}{Pr(demographic_k^{survey})}$. The updated weight is multiplied by the last ratio until the means in the survey are reasonably close to those of the CPS and IDC. The descriptive statistics of the initial, reweighted, and target mean of participants in the smartphone market and their owned laptop shares are presented in Tables S.IV. On average, the reweighted sample is one year younger, has an income that is \$536 lower, education levels that are almost similar, and 2% fewer females compared to the CPS. The reweighted shares of owned laptops are similar to the IDC average, with the highest difference being 0.1%. This allows us to use the survey data to connect the smartphone and laptop markets.

S.4. CONDITIONAL DISTRIBUTION OF SMARTPHONE PURCHASES

FIGURE S.1.—Conditional distribution of smartphone purchases



Smartphone Year	2023	2022	2021	2020	2019	2018	2017	2016	2015	2014	2013	2012	2011	2010
2018	0	0	0	0	0	3.1	2	1.7	0.56	2.3	0.73	0.27	0.0058	0.28
2019	0	0	0	0	1.5	2	2.4	2.2	0.73	2	0.13	0.33	0	0.27
2020	0	0	0	3.2	2.4	2.9	1.2	1.6	3.1	0.2	0.73	0.075	0	0.11
2021	0	0	2.6	4.2	2.5	1.9	1.9	2	0.7	0.38	0.41	0.02	0.0058	0.02
2022	0	4.3	4.5	4.9	2	1.8	1	1.6	0.19	0.75	1.1	0	0	0.028
2023	6.4	6.6	2.3	3.4	1	0.61	0.24	0.16	1.5	0.58	0.23	0	0	0

Note: Total Observations = 1156.

S.5. EQUIVALENCE OF CONDITIONAL AND UNCONDITIONAL FIRM PROBLEMS

This appendix shows that, under uniform pricing, writing the firm's problem using (i) demand conditional on laptop type c, (ii) the unconditional aggregate demand, or (iii) the expected profit across laptop types leads to identical first-order conditions for prices. It then characterizes the benchmark in which the firm can set type-specific prices, against which the equivalence becomes informative.

S.5.0.0.1. *Setup.* Let $s_j(p \mid c)$ denote the market share of smartphone j among consumers owning laptop c, and let $P(c)$ be the population share of type-c consumers. The unconditional market share is

$$s_j(p) = \sum_c P(c)\, s_j(p \mid c).$$

Firm f sets a single price p_j that applies to all consumers regardless of their laptop type. Marginal cost mc_j is independent of c.

S.5.0.0.2. *Three equivalent representations of the firm's problem.* The firm's profit can be written in three ways. The unconditional aggregate representation is

$$\pi^f_{\text{agg}}(p) = \sum_{j \in S^f} (p_j - mc_j)\, s_j(p)\, M.$$

The conditional representation aggregates type-by-type profits:

$$\pi^f_{\text{cond}}(p) = \sum_c P(c) \sum_{j \in S^f} (p_j - mc_j)\, s_j(p \mid c)\, M.$$

The expected-profit representation writes the firm's objective as the expectation over laptop types of the type-conditional profit:

$$\pi^f_{\text{exp}}(p) = \mathbb{E}_c \left[\sum_{j \in S^f} (p_j - mc_j)\, s_j(p \mid c)\, M \right] = \sum_c P(c) \sum_{j \in S^f} (p_j - mc_j)\, s_j(p \mid c)\, M.$$

By construction $\pi^f_{\text{cond}}(p) = \pi^f_{\text{exp}}(p)$, and substituting $s_j(p) = \sum_c P(c)\, s_j(p \mid c)$ into $\pi^f_{\text{agg}}(p)$ yields $\pi^f_{\text{agg}}(p) = \pi^f_{\text{cond}}(p)$. The three representations therefore share the same first-order conditions:

$$\frac{\partial \pi^f}{\partial p_j} = \sum_c P(c) \left[s_j(p \mid c) + (p_j - mc_j) \frac{\partial s_j(p \mid c)}{\partial p_j} \right] = s_j(p) + (p_j - mc_j) \frac{\partial s_j(p)}{\partial p_j} = 0.$$

The economic content of this equivalence is that the firm internalizes the composition of laptop ownership through the aggregate elasticity $\partial s_j(p)/\partial p_j$, which already integrates over $P(c)$. Whether the firm is interpreted as maximizing aggregate profit, summing conditional profits, or maximizing expected profit across laptop types is irrelevant: the optimal price is the same.

S.5.0.0.3. *Role of uniform pricing.* The equivalence relies on the constraint that p_j does not vary with c. Suppose instead that the firm could set type-specific prices p_{jc}. The unconditional and conditional representations would then yield different problems. The firm would solve, separately for each type,

$$\max_{p_{jc}} \sum_{j \in S^f} (p_{jc} - mc_j)\, s_j(p_c \mid c)\, M,$$

with first-order conditions

$$s_j(p_c \mid c) + (p_{jc} - mc_j) \frac{\partial s_j(p_c \mid c)}{\partial p_{jc}} = 0,$$

yielding type-specific markups that depend on the type-conditional elasticity $\partial s_j(p_c \mid c)/\partial p_{jc}$ rather than the aggregate. Apple-laptop owners, who exhibit inelastic demand for Apple smartphones through compatibility, would face higher markups; non-Apple laptop owners would face lower markups. Uniform pricing prevents this and forces the firm to charge a single markup against the population-weighted elasticity.

S.5.0.0.4. *Implication.* Under uniform pricing, the firm has no instrument to differentially adjust prices across laptop types and therefore does not internalize cross-market effects beyond what the aggregate elasticity already captures. The static Bertrand-Nash equilibrium is in this sense complete: there is no additional channel through which firms could exploit cross-market demand composition without departing from the uniform-pricing assumption. The equivalence among the three representations confirms that conditioning the firm's problem on laptop type is purely a notational choice in the present framework and carries no behavioral implication for equilibrium prices.

S.6. SENSITIVITY TO THE LAPTOP OWNERSHIP DISTRIBUTION

The counterfactual exercises condition on the survey-based distribution of laptop ownership, $P(c)$. Because compatibility is defined for a smartphone–laptop pair, changing $P(c)$ changes the distribution of laptop endowments against which smartphone choices are evaluated. I assess the sensitivity of the results by perturbing the laptop-ownership distribution one brand at a time. For each laptop brand, I scale its ownership weight by either 1.05 or 0.95, renormalize the remaining ownership weights within market to sum to one, hold all estimated parameters fixed, and re-solve the equilibrium. I then recompute prices, market shares, firm profits, and consumer surplus relative to the unperturbed equilibrium. I run this exercise under both compatibility regimes: the closed-ecosystem regime observed in the data and the open-ecosystem counterfactual.

Two patterns emerge. First, the Apple-laptop perturbation changes sign across compatibility regimes. Under the closed regime, increasing the Apple-laptop ownership weight raises Apple smartphone profits and prices, while reducing rival smartphone profits. Under the open regime, the same perturbation reduces Apple smartphone profits and benefits rival smartphone producers. This sign reversal reflects the compatibility channel. When compatibility is closed, Apple-laptop ownership gives Apple smartphones an exclusive compatibility advantage. When compatibility is opened, that exclusive advantage is removed, so additional Apple-laptop owners no longer reinforce Apple smartphone demand.

Second, the magnitudes are small. In the open-ecosystem counterfactual, the Apple-laptop perturbation changes Apple smartphone profits by at most about 1.1% of open-regime baseline profit, and in most years by less than one percent. These changes affect the magnitude of the open-ecosystem effects but do not alter their qualitative pattern across years. Inside-good share is essentially unchanged, and across all perturbed brands the consumer-surplus gain from opening ecosystems changes by at most 0.8%, with the largest response on the Apple-laptop margin. The responses to the 1.05 and 0.95 scalings are also approximately symmetric, indicating that the perturbations are local. The counterfactual conclusions are therefore not driven by the precise empirical realization of $P(c)$, but by the estimated compatibility valuation and the change in the compatibility regime.

TABLE S.V

SENSITIVITY OF APPLE SMARTPHONE OUTCOMES TO APPLE-LAPTOP OWNERSHIP

	Closed ecosystem			Open ecosystem		
Year	Δprice ($)	$\Delta\pi_{\text{Apple}}$ ($M)	%	Δprice ($)	$\Delta\pi_{\text{Apple}}$ ($M)	%
2018	0.58	181.4	$+0.6$	0.32	-52.7	-0.2
2019	0.13	23.6	$+0.1$	-0.11	-209.8	-0.8
2020	0.37	252.2	$+0.9$	-0.13	-169.7	-1.1
2021	0.86	293.9	$+1.1$	0.02	-184.8	-0.8
2022	0.97	270.4	$+1.1$	0.19	-53.7	-0.2
2023	1.54	318.1	$+1.1$	-0.05	-144.9	-0.6

Note: The table reports the effect of scaling the Apple-laptop ownership weight by 1.05, with remaining ownership weights renormalized within market. Each entry is the change relative to the unperturbed equilibrium under the same compatibility regime. Percentages are relative to Apple smartphone profit in that regime. Scaling the Apple-laptop ownership weight by 0.95 produces near-mirror-image responses.

S.7. DEMAND ELASTICITIES AND DIVERSION RATIOS

Table S.VI presents the price elasticities for the top ten smartphones in 2018. As expected, the diagonal values are negative and large in absolute value, indicating that a one-percent change in the price of a smartphone leads to a 2.4–6.7 percent change in its demand. Cross-elasticities are positive and lower than own-price elasticities, with closer competitors being more sensitive to price changes. For example, the cross-elasticity of the iPhone X with the iPhone 8 Plus is 0.01, while with the iPhone XR it is 0.44.

TABLE S.VI

DEMAND ELASTICITIES WITH RESPECT TO PRICE- 2018 TOP 10 PRODUCTS

	iPhone X	iPhone 8	iPhone 8 Plus	iPhone XR	iPhone XS Max	iPhone XS	Galaxy S9	Galaxy S9+	iPhone 7	Aristo 2
iPhone X	-5.7170	0.0475	0.0123	0.4444	0.0000	0.0001	0.0001	0.0004	0.0011	0.0493
iPhone 8	0.2263	-4.9079	0.0278	0.2523	0.0000	0.0003	0.0001	0.0009	0.0026	0.0280
iPhone 8 Plus	0.2300	0.1094	-6.6685	0.2622	0.0000	0.0003	0.0001	0.0009	0.0026	0.0272
iPhone XR	0.4006	0.0477	0.0126	-6.7132	0.0000	0.0001	0.0001	0.0004	0.0011	0.0472
iPhone XS Max	0.0620	0.0332	0.0071	0.0637	-2.4742	0.0056	0.0000	0.0002	0.0007	0.0095
iPhone XS	0.0620	0.0332	0.0071	0.0637	0.0007	-2.4694	0.0000	0.0002	0.0007	0.0095
Galaxy S9	0.2292	0.1095	0.0287	0.2597	0.0000	0.0003	-6.1871	0.0009	0.0026	0.0275
Galaxy S9+	0.2295	0.1094	0.0288	0.2606	0.0000	0.0003	0.0001	-6.3567	0.0026	0.0274
iPhone 7	0.2282	0.1095	0.0284	0.2568	0.0000	0.0003	0.0001	0.0009	-5.6718	0.0277
Aristo 2	0.3348	0.0400	0.0099	0.3557	0.0000	0.0001	0.0000	0.0003	0.0009	-4.4563

Table S.VII provides the diversion ratio with respect to price for the top ten smartphones in 2018. The diversion ratio indicates the proportion of consumers who, in response to an increase in product j's price, stop purchasing j relative to those who leave j and purchase k instead. Following Conlon and Mortimer (2021), the diagonal represents diversion to the outside good. As expected, there is a lower diversion ratio to highly differentiated products, such as the iPhone X with the XS Max, compared to the iPhone XR. Most cross-brand diversion ratios are extremely low (e.g., iPhone with Galaxy); however, while consumers who own Apple laptops have no compatibility with the Galaxy S9+ or Aristo 2 (Motorola), the diversion ratio for the latter can be higher than for some Apple products due to independent smartphone characteristics. The diversion ratio to the outside good is also very high for the iPhone XS Max and XS, the most expensive smartphones in the table, arguably because of their distinct, independent features. The small diagonal entries reflect limited diversion to the outside good rather than weak substitution: because smartphones are near-essential, most displaced consumers substitute to another smartphone rather than the outside option.

TABLE S.VII

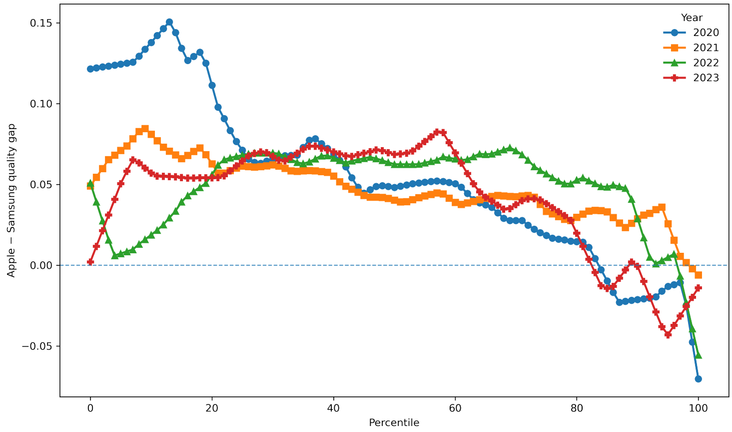
DIVERSION RATIO WITH RESPECT TO PRICE- 2018 TOP 10 PRODUCTS

	iPhone X	iPhone 8	iPhone 8 Plus	iPhone XR	iPhone XS Max	iPhone XS	Galaxy S9	Galaxy S9+	iPhone 7	Aristo 2
iPhone X	0.0032	0.0102	0.0019	0.0657	0.0000	0.0002	0.0000	0.0001	0.0002	0.0122
iPhone 8	0.0374	0.0080	0.0041	0.0353	0.0001	0.0005	0.0000	0.0001	0.0005	0.0066
iPhone 8 Plus	0.0385	0.0226	0.0064	0.0371	0.0001	0.0004	0.0000	0.0001	0.0005	0.0065
iPhone XR	0.0706	0.0104	0.0020	0.0029	0.0000	0.0002	0.0000	0.0001	0.0002	0.0118
iPhone XS Max	0.0030	0.0020	0.0003	0.0026	0.4365	0.0022	0.0000	0.0000	0.0000	0.0006
iPhone XS	0.0030	0.0020	0.0003	0.0026	0.0003	0.4373	0.0000	0.0000	0.0000	0.0006
Galaxy S9	0.0379	0.0223	0.0043	0.0363	0.0001	0.0004	0.0067	0.0001	0.0005	0.0064
Galaxy S9+	0.0381	0.0224	0.0043	0.0365	0.0001	0.0004	0.0000	0.0066	0.0005	0.0064
iPhone 7	0.0374	0.0221	0.0042	0.0356	0.0001	0.0004	0.0000	0.0001	0.0071	0.0064
Aristo 2	0.0530	0.0078	0.0014	0.0476	0.0000	0.0002	0.0000	0.0000	0.0002	0.0033

Note: The diagonal represents the diversion to the outside good.

S.8. APPLE-SAMSUNG SMARTPHONE HARDWARE QUALITY GAP BY PERCENTILE

FIGURE S.2.—Apple-Samsung smartphone hardware quality gap by percentile



Note: The figure reports the difference between Apple and Samsung smartphone quality across percentiles. Positive values indicate that Apple quality is higher at a given percentile, while negative values indicate that Samsung quality is higher. Apple quality exceeds Samsung's across most of the distribution; Samsung is higher only in the top percentiles. Over 2020–2023 the negative gap in those top percentiles narrows—Apple catches up where Samsung leads—reducing Apple-laptop owners' incentive to switch to Samsung.

S.9. MINIMUM OPEN ECOSYSTEMS

TABLE S.VIII

MINIMUM OPEN ECOSYSTEMS – AVERAGE FIRM EFFECT ACROSS YEARS

Firm	ΔInside good share	ΔSmartphone price	ΔFirms profit	ΔCS
Apple	0.0472	21.15	4,651.05	197.94
LG	-0.0086	-6.85	-228.46	682.98
Motorola	-0.0076	-5.47	-190.30	643.35
Samsung	-0.0175	-16.07	-1,037.89	775.11

Note: Profit and CS are in millions.

S.10. SAMSUNG-HP MERGER

TABLE S.IX

SAMSUNG-HP MERGER - AVERAGE EFFECT ACROSS FIRMS

Market	ΔInside good share	ΔApple share	ΔSmartphone price	ΔFirms profit	ΔCS
2018	-0.0049	-0.0927	37.12	762.15	3,402.64
2019	-0.0014	-0.1676	58.23	1,861.59	1,888.97
2020	0.0090	-0.0937	64.81	1,727.50	2,144.84
2021	0.0405	-0.0532	-0.07	-46.70	2,212.73
2022	0.0187	-0.0434	-0.55	-376.68	2,402.46
2023	0.0562	-0.0092	-18.31	-765.68	2,729.92

Note: CS refers to consumer surplus. Profit and CS are in millions. ΔInside good share includes Apple.

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