Cross-Product Compatibility, Lock-In, and Market Power: The Case of Smartphones and Laptops*

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Abstract

This paper examines the role of compatibility across *standalone* technology products in anchoring consumers to brands. Through a novel experimental design, I identify the causal impact of compatibility, showing that participants' willingness to pay for smartphones increases by 9% of their retail price when compatible with a laptop. I combine the experimental results with a smartphone demand model that incorporates compatibility with laptops to assess the welfare effects of *(i)* regulations mandating cross-brand compatibility ("open ecosystems") and *(ii)* cross-market mergers. I find that in 2018-2019, closed ecosystems benefit Samsung by locking non-Apple laptop owners into lower-quality Samsung smartphones, while the switch to open ecosystems boosts Apple's smartphone market share. However, in 2020-2023, closed ecosystems benefit Apple, as Samsung's top smartphones are superior, prompting Apple laptop owners to switch to Samsung smartphones in open ecosystems. In both periods, consumer surplus rises due to lower prices and greater product variety in open ecosystems. A counterfactual merger between Samsung and HP, Apple's main smartphone and laptop competitors, respectively, results in lower smartphone market concentration but raises Samsung smartphone prices, disadvantaging consumers who value compatibility less.

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"Tie all of our products together, so we further lock customers into our ecosystem"

(Steve Jobs, former Apple CEO).

1 Introduction

How compatibility across *standalone* technology products, such as smartphones, laptops, and smartwatches, affects demand remains unexplored in the literature but could significantly shape consumer welfare and amplify market power. For instance, consumers seeking compatibility features like cross-device copy-paste may be driven to purchase Apple smartphones if they own Apple laptops, while Windows users would prefer Samsung devices.

Should regulators mandate cross-brand compatibility (i.e., "open ecosystems") when firms produce non-substitute standalone technology products, such as smartphones and laptops? This question is timely, given the Department of Justice's (DOJ) lawsuit against Apple in March 2024, alleging that Apple is tethering consumers to its ecosystem. *Ex-ante*, the impact of open ecosystems is ambiguous: they allow consumers to benefit from cross-product compatibility without being locked into a single ecosystem—boosting product variety, reducing switching costs, and enhancing consumer surplus (Farrell and Klemperer, 2007). However, open ecosystems may also raise prices if demand expands more than competition, reducing surplus for those who value compatibility less (Matutes and Regibeau, 1988). Furthermore, open ecosystems could increase smartphone market concentration by enabling non-Apple laptop users to purchase Apple smartphones while benefiting from compatibility, potentially amplifying Apple's smartphone dominance and leading to higher prices.

Regulators typically overlook cross-market mergers, viewing them as affecting only individual product markets (e.g., the DOJ's 2014 report on Lenovo's acquisition of Motorola). However, cross-market mergers warrant attention, as cross-product compatibility has become increasingly significant. This raises the question: What is the welfare effect of a cross-market merger? *A priori*, the impact of such mergers is ambiguous: they can enhance compatibility and eliminate double marginalization by increasing demand in complementary markets (Song et al., 2017; Ershov et al., 2018). However, the merged firm may exploit consumers locked to its ecosystem to raise prices and enforce incompatibility 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 through five steps. First, I establish the causal effect of compatibility on demand using a novel experimental design where participants report their willingness to pay (WTP) for a smartphone conditional on being given a laptop. By varying the brand of the awarded laptop, the design generates smartphone-laptop pairs with different compatibility levels. The difference in smartphone WTP when the laptop is of the same brand identifies the causal impact of compatibility. Second, using the experimental results, I construct a smartphone demand model incorporating compatibility with laptops. Prices in this model are set in a static Nash-Bertrand equilibrium. Third, I estimate the model using repeated cross-sectional market data from the International Data Corporation (IDC) Tracker (2018-2023), alongside a proprietary compatibility index and a survey on product ownership that I administer. In the estimation, I utilize a unique micro-moment matching difference in WTP from the experiment with compatibility. Fourth, I evaluate the implications of an open-ecosystems counterfactual, allowing compatibility across ecosystems. Fifth, I analyze the effects of a counterfactual 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 I conduct serve four crucial purposes. First, typical market data is cross-sectional, offering only a snapshot in time and limiting its ability to link the smartphone and laptop markets. Thus, revealing consumers' ownership patterns becomes essential for connecting these markets. Second, the experiment provides a direct measurement of WTP for smartphone-laptop compatibility, which otherwise cannot be disentangled from consumer preference, the brand-fixed effect, and loyalty. Third, the survey allows for the construction of two key quantifications essential to the demand model:

(i) an estimate of the smartphone market size by leveraging purchase recurrence data; *(ii)* using the relationships between consumers' purchasing behaviors and demographic attributes to employ a non-parametric distribution of consumer characteristics. Fourth, the survey reveals two stylized facts: *(i)* agents participate in one market at a time; *(ii)* consumers are myopic when purchasing smartphones, disregarding future laptop costs.

The experiment shows that compatibility significantly causally impacts smartphone demand. The design elicits WTP for smartphones in an incentivized market, with each WTP conditional on winning a laptop lottery prize. In line with experimental best practices, the price paid for smartphones is randomly drawn, ensuring that participants report their true WTP. When participants report a lack of awareness regarding compatibility, the difference in the average WTP for compatible smartphones is a statistically insignificant \$7. Given that smartphones are durable and high-cost products typically researched by consumers, while the experiment uses a random pool that may be uninformed, I provide participants with compatibility information. When participants are aware of compatibility features, the difference in WTP between compatible and incompatible smartphones is a significant \$75, i.e., 9% of smartphone retail price ($p < 0.01$).

Consequently, I develop and estimate a structural model of smartphone demand that incorporates compatibility with laptops, using the experimental measure of WTP for compatibility as a micro-moment. This model enables an evaluation of how compatibility influences consumers' smartphone purchase decisions, revealing that they place significant value on both hardware and compatibility features, consistent with experimental findings.

I evaluate the welfare implications of open-ecosystems counterfactual, where any smartphone-laptop pair is compatible. The results show that in 2018-2019, when Apple's smartphones significantly surpass Samsung's in hardware quality, the closed ecosystems benefit Samsung because non-Apple laptop owners are locked into low-quality Samsung smartphones. Open ecosystems drive consumers who have been loyal to Samsung's ecosystem to switch to Apple smartphones due to the latter's higher compatibility index. This shift increases market concentration and boosts Apple's profits while negatively affecting its competitors. However, from 2020 to 2023, the closed ecosystem benefits Apple as the hardware quality gap narrows. Open ecosystems result in Apple laptop owners opting for Samsung smartphones, as compatibility remains constant while Samsung's top devices exceed Apple's hardware quality. In both time frames, consumer surplus increases due to lower prices and a broader variety of compatible products.

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 leads to an increase in the merged entity's prices due to increased cross-market power that ties consumers to its ecosystem while also boosting its smartphone market share at the expense of Apple, resulting in lower smartphone market concentration. Although the merger raises mean consumer surplus, the rise in the merged entity's prices reduces the surplus for those who value compatibility less. Samsung-HP remains indifferent to incompatibility with Windows laptops, as the superior average hardware quality of Samsung smartphones, compared to non-Apple, sustains smartphone demand regardless of compatibility.

This paper contributes to four branches of literature. First, it expands the growing empirical research on opening ecosystems. Prior studies have focused exclusively on the impact of open ecosystems on add-on products, finding varied effects on welfare (Lee, 2013; Huang, 2022; Li, 2023). Incompatibility of add-on products leads to zero utility and exclusion from consumers' consideration sets, whereas incompatible *standalone* products can still provide positive value. Thus, the analysis of compatibility effects is distinct for standalone products, as compatibility adds to consumers' utility beyond the inherent utility of each product, depending on smartphone choice and owned laptops. This paper extends the literature by *(i)* revealing how ecosystems influence demand for standalone products, a factor previously attributed to brand preference and loyalty, *(ii)* examining non-binary connectivity that affects product compatibility index, and *(iii)* demonstrating the previously unobservable role of owned laptops in determining consumers utility from smartphones.[1]

[1]For further details on distinguishing unobserved heterogeneity from state-dependent preferences, see, for example, Pakes et al. (2021), which develops a choice model incorporating state dependence while allowing for unobserved heterogeneity in individual-good fixed effects. This model examines health insurance plan choices without accounting for the mechanism driving state dependence.

Second, this paper enhances the quantitative understanding of cross-market mergers when products can be consumed both independently and together. Previous empirical studies examining cross-market mergers of standalone products yield varying effects on price due to cross-market power (Song et al., 2017; Ershov et al., 2021; Wang, 2021). This study advances the literature by focusing on a cross-market merger driven exclusively by compatibility between standalone products, a factor overlooked by current antitrust policies, rendering them ineffective for addressing cross-market mergers involving technology firms. Additionally, by analyzing the compatibility decisions of the merged firm in relation to competitors' products, this paper contributes to the expanding literature on endogenous goods (Berry et al., 2016; Wollmann, 2018; Crawford et al., 2019).

Third, this paper contributes to the empirical literature on smartphone and laptop markets. Eizenberg (2014) examines the impact of CPU innovation on product variety in the personal computer market, while Fan and Yang (2020) investigates the smartphone market. Both studies use data before compatibility is introduced. While this study does not estimate product variety, it extends the literature by revealing the demand interdependence between smartphones and laptops through compatibility. This interdependence affects firms' cost structures and product variety estimations. Additionally, demonstrating the demand dependency, the paper shows how firms leverage power across markets.

Fourth, this paper contributes to the growing trend of using experimental designs to identify structural parameters (e.g., Heckman (2000) for causal analysis). Pakes (2021), in reviewing the empirical industrial organization (IO) literature, contends that structural models often struggle to *"distinguish between correlations in tastes and causal factors that lead to similar actions."* In this framework, simply observing smartphone and laptop purchases is insufficient to determine whether consumers buy devices due to causal cross-product compatibility. While the experiment highlights the importance of compatibility, one may suspect that compatibility between smartphones and laptops may not impact demand, as it imposes no additional cost on consumers, and the literature provides no evidence of connectivity binding consumers to standalone products. Ershov et al. (2021) cleverly uses only observational data to distinguish between correlation and causality, offering spatially suggestive evidence of suppliers' joint pricing strategies.

Conflating causality with correlation can lead to costly errors, such as perpetuating closed ecosystems. In response, I follow Pakes' advocacy for ensuring causal inference. Since instrumental variables are unavailable in this context, I instead employ a novel experimental design that exogenously varies cross-product compatibility. Additionally, I leverage participants' differences in WTP due to compatibility as a unique micro-moment in the structural model, enabling a robust causal analysis.

The remainder of the paper proceeds as follows. Section 2 describes the experiment that examines the causal relationship between compatibility and demand. Section 3 introduces the compatibility index, repeated cross-sectional data, and survey used to construct the structural model. Section 4 describes the model, while Section 5 outlines the estimation approach and results, and Section 6 presents the counterfactual analysis.

2 Experiment: separating compatibility from taste correlation.

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 brand-fixed effects and loyalty. However, product compatibility can shape purchasing decisions, turning what might seem like a correlation in preferences—such as choosing a smartphone brand to match an already-owned laptop or attributing purchases to brand-fixed effects and loyalty—into a causal effect driven by cross-device compatibility.

I design an experiment to examine whether compatibility influences demand for standalone goods and to estimate participants' valuation of compatibility. The experiment randomly assigns laptops and a monetary prize using a lottery, followed by eliciting participants' WTP for a smartphone. By varying the laptop brands, which directly affect cross-device compatibility, I assess how compatibility causally influences participants' WTP for a smartphone. Participants can win either an Apple or Samsung laptop and then state their WTP for an Apple or Samsung smartphone.

2.1 Consumer decision

Consider consumer i, who owns laptop c, with the following indirect quasi-linear utility from smartphone $j \in S$,

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

where V_{ij} and W_{ijc} represent the independent values (e.g., screen size) and the dependent values derived from smartphone j's compatibility with laptop c, respectively. By definition, V_{ij} and W_{ijc} in Equation (1) are additively separable, meaning the contribution of the independent values to utility does not depend on the dependent ones. P_{ijc} is the price consumer i pays for smartphone j when they own laptop c. With a slight abuse of notation, this price may also be equivalent to $P_{ij\cdot}$, which denotes the price that consumer i pays for smartphone j when they own any other laptop, regardless of compatibility.

Assume that smartphone j is compatible with laptop c but not with c'. If consumer i values compatibility, then her utility from the compatible smartphone j is at least as high as her utility from the same smartphone when it is incompatible:

$$\begin{aligned} u_{ijc} &\geq u_{ijc'} \\ W_{ijc} - P_{ijc} &\geq -P_{ijc'} \\ W_{ijc} &\geq P_{ijc} - P_{ijc'} \end{aligned}$$

The second inequality arises from the incompatibility between smartphone j and laptop c', where $W_{ijc'} = 0$. Thus, $P_{ijc} - P_{ijc'}$ represents the price consumer i pays for compatibility, net of the value independent of laptops. Therefore, if $P_{ijc} - P_{ijc'} > 0$, consumer i values compatibility.[2] Consequently, I examine the difference in prices consumers pay for smartphone j when it is compatible with laptop c versus when it is incompatible with c'.

[2]Equality can hold when the outside good value (U_0) remains unaffected by compatibility: $u_{ijc} = V_{ij} + W_{ijc} - P_{ijc} = U_0 \rightarrow P_{ijc} = V_{ij} + W_{ijc} - U_0, P_{ijc'} = V_{ij} - U_0$. Therefore, $W_{ijc} = P_{ijc} - P_{ijc'}$.

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 value of a 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. As described in Equation (2), if the lottery winner's WTP is lower than the randomly drawn price, they receive \$4 participation fee, the laptop, and the \$RP; otherwise, the winner acquires the \$4 participation fee, laptop, smartphone, and a cash payment equal to the difference between the smartphone's RP and the randomly drawn price. Participants see identical WTP questions, with the elicitation order randomized to avoid the order effect, where earlier questions might influence responses to later ones.

$$\text{payoff} = \begin{cases} \$4, & \text{if not winning the lottery;} \\ \$4 + \textit{laptop} + \$RP, & \text{if win the lottery \& WTP} < p; \\ \$4 + \textit{laptop} + \textit{smartphone} + (\$RP - \$p), & \text{if win the lottery \& WTP} \geq p. \end{cases} \tag{2}$$

The WTP only determines whether, in addition to a laptop, the subject's payoff is \$RP or smartphone + (\$RP - \$p). However, the cash prize (\$RP - \$p) depends on the randomly drawn price, p, rather than the WTP; therefore, a participant's best response is to report their true value for smartphones. This design is a modification of the Becker et al. (1964) mechanism, which is extensively used in the literature to estimate participants' WTP and is proven to be incentive-compatible, meaning participants' weakly dominant strategy is to offer their true value.[3] The instructions explain to participants that they are incentivized to report their true value using examples that do not include smartphone purchases to avoid the anchoring effect on their offers.

Since only the laptop lottery winner has the option to purchase a smartphone, while participants are notified that the draw takes place after the experiment is finished, participants must treat the WTP questions as if they win the lottery. Additionally, since participants are told that one of the questions is randomly drawn after the experiment, participants must treat WTP elicitations independently as if each one is pulled. This procedure is a modification of the Coffman and Niehaus (2020) mechanism, which examines the effect of persuasion and self-interest on participants' WTP.

Goods vary throughout the experiment, but the selected products have the same retail prices: Apple and Samsung laptops retail for \$999, and smartphones for \$799. Therefore, varying the brand of the laptop lottery prize while offering the option to buy the same smartphone only affects product compatibility.

Smartphones are durable and expensive items that consumers typically research before purchasing. However, participants may be unfamiliar with the devices' attributes since the experiment uses a random sample rather than individuals planning to enter the smartphone market beforehand. To address participants' potential lack of knowledge about compatibility, the WTP elicitation segment concludes by providing participants with smartphone-laptop compatibility features information and then eliciting their offers.

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

[3] More recently, this mechanism is used to reveal the true WTP for clean water in Ghana (Berry et al., 2020).

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 feel compelled to increase their WTP after receiving compatibility information, interpreting each additional piece of information as inherently positive. If this is the case, we would expect inflated WTPs that do not reflect participants' true preferences when provided with three pieces of compatibility information—i.e., an anchoring effect might occur between the initial set of questions without compatibility information and the subsequent set with it. To test for this effect, participants are randomly assigned to one of two groups: the first group answers WTP questions first without and then with compatibility information, while the second group answers WTP questions only with compatibility information.

Participants' performance incentives are generally higher than in previous studies using Prolific. The incentives in my experiment are straightforward to calculate: The probability of winning the lottery is 0.001. There is a maximum of eight questions contingent on the lottery payment (a small group observes only four WTP questions with compatibility information), and prize values range from $1,799 to $2,597. Thus, the expected value of WTP questions is between $1.76-$2.96, with the expected value per WTP question between $0.22 and $0.37, irrespective of the participation fee. The payment exceeds or aligns with rates reported in the literature, ensuring participants are incentivized to report their WTP thoughtfully.[4] Additionally, participants complete a set of comprehension questions to verify their understanding of the payment mechanism when their WTP is lower or higher than the randomly drawn price, p. On average, participants spend 3.3 minutes on these questions, with those having a higher WTP for compatible smartphones demonstrating a lower ratio of time spent to errors made (measured by "number of clicks") compared to those with a higher WTP for incompatible devices. Finally, since each question has an equal probability of being drawn, the low probability does not differentially influence questions with compatible or incompatible products or

[4] Exley and Nielsen (2024), which examines perspectives on gender, reports a similar average hourly participation fee of $12 but includes a lower decision-dependent random bonus payment ranging from zero to $1. I use this study as a reference point because it is conducted at the same time, suggesting that its incentive structure represents current best practices for performance incentives on Prolific.

those with and without connectivity information. Thus, any differences in agents' WTP are attributable solely to compatibility.

Before the WTP elicitation, participants are asked whether they are eligible for discounts when purchasing devices (e.g., Apple offers a $150 discount for students purchasing a computer). This helps explain WTP variation due to retail price differences. Additionally, to ameliorate participants' concerns about switching costs, including moving across ecosystems, participants are informed that professional support is provided to transfer their data to their new devices and learn about their functionalities.

2.3 WTP estimation

I estimate the effect of compatibility on participants' smartphone WTP using two measures: within- and across-subject comparisons. Since participants observe the same questions randomly, measuring the compatibility effect on WTP within and across participants is straightforward. I compare the difference in WTP within individual participants and across different participants when the offered smartphone is compatible and incompatible with the awarded laptop.

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; Eyal et al., 2021). I randomly recruit 1,000 agents who previously completed at least a thousand tasks on Prolific.[5] Sample details are presented in Table 1. 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 pay-

[5]Due to a data recording error on the platform, the analysis could only use 992 participants. The results are insensitive to this.

Table 1: Demographic descriptive statistics

Category	Mean	SD	Min	Max
Age	40.65	10.46	20.00	67.00
Income	\$59,090.90	\$41,518.14	\$2500.00	\$150,000
Education	14.97	2.16	10.00	20.00
Gender	Male = 588, Female = 394, Prefer not to say = 10			

ment of \$4, substantially higher than the minimum hourly payment for participants on Prolific, which is \$8, along with any prizes they win. This pool of participants, along with an additional 118 respondents (62 males and 56 females) who do not take part in the experiment, also answer the survey described in Section 3.3.

2.5 Experiment results

The first WTP elicitations for Apple and Samsung smartphones do not include a lottery for a laptop and a dollar prize, i.e., they are merely stated preference questions. Consistent with the literature that finds participants tend to overstate goods' valuation when not incentivized (Norwood et al., 2007; De Corte et al., 2021), the results show that participants' average WTP is higher without a lottery than with one. Since participants' WTPs without the payment mechanism are higher than offers with it, there is a strong justification for introducing the payment mechanism. This supports the need for the experiment design to elicit participants' true WTP.

Table 2, 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 ($p < 0.1$). I define the higher WTP for smartphones by the same laptop brand without any compatibility pre-knowledge (not just the information provided) as a *"brand matching fixed effect,"*, 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 connectivity is \$17 for Apple and \$18 for Samsung, where these differences are significant ($p < 0.01$). If participants who state "know" have full prior knowledge about compatibility features, providing these participants with connectivity information should not affect the WTP; however, as I present next, this is not the case.

Table 2, Panel B, presents the WTP with compatibility information provided to participants, controlling for participants' pre-knowledge state. Both groups exhibit an increase in their difference in WTP compared to no information provided, as seen in Table 2, Panel A. Conditional on a smartphone brand, those who report they know about connectivity beforehand (group "✓") have higher smartphone WTPs. Therefore, while the percentage difference in WTP across both groups is similar, those with compatibility pre-knowledge exhibit a greater absolute difference in WTP than those initially disclosing ignorance, \$105.27 and \$84.09 for Apple and Samsung, respectively, compared to \$75.34 and \$74.77. Difference-in-difference analysis for the absolute difference in WTP with information across knowledge states for a given brand reveals that the differences are significant for Apple but not for Samsung ($p < 0.01$), as explained below.

To further investigate the source of the absolute difference-in-difference in WTP for Apple smartphones in Table 2, Panel B, I examine participants' product ownership. The analysis reveals that participants who own an Apple product have higher WTP for Apple smartphones, indicating that WTP reflects auxiliary selection effects beyond the treatment itself. This has two explanations: first, Apple product owners have a higher than average valuation for Apple products, i.e., brand endowment effect; second, while the experiment provides the same compatibility information on Apple and Samsung products, the former has more connectivity features. Once the experiment provides participants with compatibility information, Apple owners may recall connectivity features beyond the ones provided, hence pooling the average difference in WTP for Apple higher.

Comparing Panel A and B in Table 2, it can be observed that, conditional on prior knowledge of compatibility, providing information increases WTP for compatible smartphones and decreases WTP for incompatible ones compared to the absence of such information. This demonstrates that compatibility raises participants' valuations for compati-

Table 2: 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	Compatibility pre-knowledge	N	Mean WTP compatibility	Mean WTP incompatibility	Mean difference	Mean WTP compatibility	Mean WTP incompatibility	Mean difference
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: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

ble products and lowers them for incompatible ones. The decline in WTP for incompatible smartphones with the provision of information can be attributed to the resolution of uncertainty. Participants observe WTP questions for a smartphone when the laptop brand varies while may not be fully aware of compatibility features. This can result in an overvaluation of incompatible smartphones when uninformed, misconstrue their true utility. Once this uncertainty is clarified through information provision, participants revise their WTP downward for incompatible devices accordingly.

Since reporting whether participants "know" or "did not know" about compatibility features beforehand is unincentivized, the difference in WTP—net of the "brand matching fixed effect"—must account for potentially untruthful responses. As a result, the WTP for Apple and Samsung smartphones' connectivity features, adjusted for the "brand matching fixed effect," is \$79-\$87 and \$63-\$73, respectively.

Consistent with the literature, I find that gender plays a role in WTP provision experiments. On average, the difference in WTP for females is higher than for males, primarily due to females' lower WTP for incompatible smartphones. This difference is significant only for Apple devices when compatibility information is provided (see Appendix A). This may be attributed to the relationship between choice experiments and personality traits (Grebitus et al., 2013). Similarly, Coffman and Niehaus (2020), who examines the effect of self-interest and persuasion on WTP, also finds that gender influences participants' offers.

2.5.1 Robustness check- anchoring effect

As explained in section 2.2, the experiment examines whether eliciting WTP without compatibility information influences subsequent WTP reports with compatibility information, i.e., an anchoring effect. To test the robustness of the results, I compare two groups: one provides WTP first without and then with compatibility information, while the other provides WTP only with compatibility information.

Table 3 provides the WTPs of participants who have been immediately provided with compatibility information (group "✓") and those who have been first asked to provide offers without information provision (group "✗, ✓"). The difference in participants' WTP for compatible and incompatible Apple smartphones is almost identical across the two groups, \$96. The difference in WTP for Samsung smartphones by participants who first report on WTP without information is higher by \$6.6 than participants who immediately observe connectivity features. For both Apple and Samsung, difference-in-difference analysis shows no significant anchoring effects.

Table 3: 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: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Together with the payment mechanism that ensures participants report their true WTP for smartphones, the absence of an anchoring effect supports the conclusion that participants' WTP is influenced by connectivity features rather than an experimental design that "encourages" higher offers for compatible products by introducing additional product characteristics at a later stage.

2.6 Experiment conclusion

The experiment investigates consumers' WTP for smartphones when they are compatible and incompatible with laptops. Given that laptop ownership is not randomly assigned, the experiment first randomizes laptop ownership through a lottery and then elicits participants' WTP for smartphones. By varying the laptop brand in the lottery, the experiment controls the compatibility between the offered smartphone and the owned laptop. This design enables the evaluation of the causal effect of compatibility on participants' WTP.

The experiment results show that compatibility significantly affects the demand for goods. Since the experiment uses a random sample of participants rather than those who planned to purchase smartphones in advance, participants may lack knowledge about product characteristics. When participants report they are unaware of cross-product compatibility, their average WTP for a smartphone from the same brand as the lottery laptop is an insignificant \$7. However, when participants are informed about compatibility features, the average difference in WTP is a significant \$75 ($p < 0.01$). This demonstrates that compatibility positively and significantly impacts consumers' purchasing decisions.

Therefore, I construct a structural model where compatibility influences consumers' purchasing decisions through utility. Additionally, I use agents' differences in WTP due to compatibility as a micro-moment in the structural model, as presented in section 5.

3 Data

The paper uses three data sources to estimate the effect of compatibility on the markets: *(i)* collected information on product compatibility, *(ii)* IDC's Tracker Database, and *(iii)* a survey I conducted.[6] Additionally, the paper incorporates the change 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 et al. (1995) (BLP) model, i.e., without considering complementarity. The survey incorporates micro-moments, as in Berry et al. (2004), and provides information on consumer product ownership across multiple markets. By integrating the data on the degree of compatibility between smartphones and laptops with the repeated cross-sectional market data and the survey, the paper constructs a random-coefficient demand model for smartphones, where consumers' decisions are influenced by compatibility with laptops.

[6] Eizenberg (2014) employs IDC data.

3.1 Compatibility Index

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

I collect data on cross-device compatibility within and across firms from brands' websites such as Apple, Samsung, and Microsoft. Since the availability, compatibility, and quality of third-party services connecting devices are almost impossible for consumers to track before purchasing a device, and system-level integration is generally limited to producers, this paper limits its attention to pre-installed compatibility features. I include the following compatibility features: copy-paste, automatic hotspot, phone call, text, handoff, file transfer, camera and webcam continuity, and continuity sketch.[7]

Each compatibility feature has a binary outcome. I construct a compatibility index between any two products by summing their binary connectivity features and dividing 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 (OS) 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.

[7]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.

3.2 Market data

The market data comes from IDC. It consists of a repeated cross-section of prices, quantities, and characteristics of model-level products in the smartphone market and series-level products in the laptop market sold in the U.S. between 2018 and 2023. Average shares in the smartphone and laptop markets are presented in Table 4. The smartphone market is highly concentrated, with 77% controlled by Apple and Samsung, while this percentage is shared among four firms in the laptop industry. This suggests that opening closed ecosystems may have different impacts on the smartphone and laptop markets.

Table 4: 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

The annual mean smartphone sale is 123 million units, with a standard deviation of 11 million units. The maximum sales in the sample reached 139 million units in 2018. The average annual sale per smartphone model is 1.1 million units, with a standard deviation of 2.3 million—more than double the mean—indicating significant variation in model sales. Table 5 summarizes smartphone prices and hardware characteristics. The average smartphone is priced at approximately \$430, with a substantial standard deviation of \$390. The dataset includes each smartphone's brand, model, number of processor cores, screen size (in inches), camera resolution (in megapixels), storage capacity (in GB), and processor speed (in GHz). The standard deviation of these characteristics ranges from 0.11% to 114% of their respective means, indicating a wide variety of smartphones in the sample.

Table 5: Smartphones characteristics- summary statistics

Variable	Mean	SD	Min	Max
Prices ($)	428.00	390.65	12.50	1600.00
Processor cores	6.53	1.83	2.00	8.00
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		

The structural model analysis examines smartphone purchases conditional on owned laptops. However, the paper does not analyze laptop purchases conditional on smartphones due to limitations in data quality: the data only partially links laptop characteristics to specific product series.

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 et al. (2019) and Stantcheva (2023). I survey both 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.[8] 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 survey also gathers information on participants' second-best choice, which is used to construct a micro-moment.

[8]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/`.

Since the survey uses a random sample, I reweigh the sample to match the CPS mean and IDC share, as described in Appendix B. The demographic characteristics of the entire survey sample are presented in Table 6 and Figure 1. On average, the survey 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%).

Table 6: Descriptive statistics: demographic and owned laptop

Panel A: Demographic		**Panel B: Owned laptop**	
Demographic	Mean	Brand	Share
Age	42.34 (13.59)	HP	0.30
Income	$52,409.33 (44,178.67)	Apple	0.27
Education	14.05 (2.44)	Lenovo	0.16
Gender	1.50 (0.50)	Dell	0.10
		Acer	0.08
		Asus	0.07

Note: Standard deviations are in parentheses.

3.3.1 Samrtphone 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, since IDC data reports a maximum annual sales volume of 139 million units, I adjust the market size accordingly. 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.

While participants acquire products at different periods, it is important to examine whether consumers are myopic about a future laptop when constructing the structural model. Only 7.1% of participants report considering the cost of a future laptop when purchasing a smartphone. The survey does not directly ask participants whether they consider the ecosystem of a future product when choosing a current device. This is because the survey, which is not incentivized, is administered after the experiment that provides compatibility information, potentially distorting responses.[9] Therefore, I construct a static model in which consumers' decisions depend on ownership of a complementary good without being forward-looking.

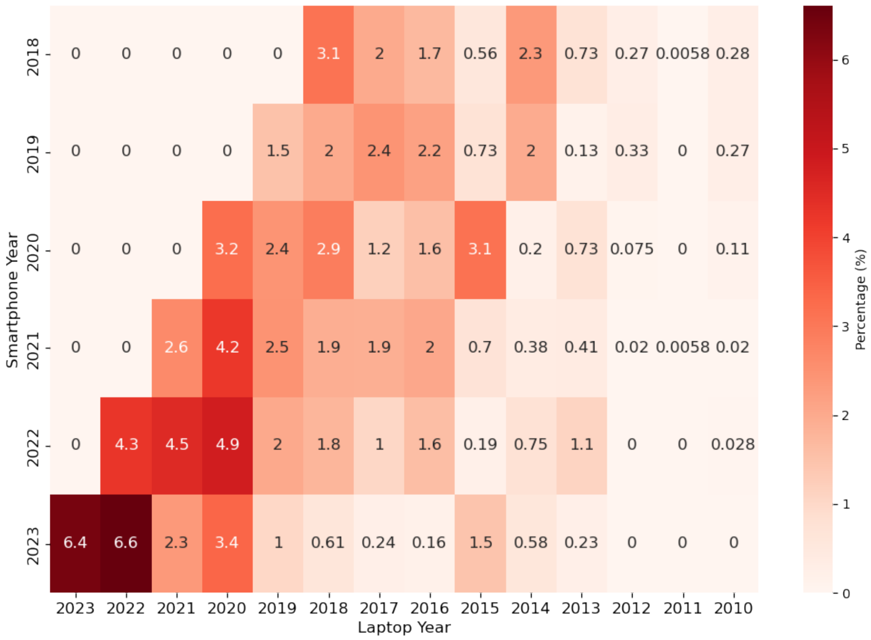
3.3.2 Evidence for compatibility effects

As illustrated by the compatibility index, the purchasing year of a pair of products is related to the goods' connectivity. Figure 1 shows the distribution of smartphone purchases conditional on the procurement years of owned laptops. The diagonal, along with its immediate neighbors, reveals that most consumers acquire smartphones when their laptops are zero to three years old. This suggests that most consumers benefit from product compatibility when the paired goods belong to the same ecosystem.

Survey results on agents' conditional smartphone brand choices align with the experimental findings, emphasizing the potential importance of product compatibility for consumers in the real market, rather than just in a controlled experiment, and its influence on market power. Table 7, Panel A, provides the probability of consumers choosing a smartphone brand, while Panel B shows the probability conditional on laptop ownership.

[9] As evidence of the experiment's effect on survey responses, in pilot studies with different question orders, only 1% of participants are forward-looking.

Figure 1: Conditional distribution of smartphone purchases



Note: Total Observations = 1156.

In Panel A, the average probability of purchasing an Apple smartphone between 2018 and 2023 is 0.50, the highest in the market. However, conditional on owning an Apple laptop, the probability of purchasing an Apple smartphone in Panel B increases by 62% to 0.82, further solidifying Apple's position as the market leader. Given Apple's closed ecosystem, this substantial increase in purchasing probability underscores the potential importance of compatibility for consumers using non-experimental data. Additionally, this increase in purchase probability demonstrates how firms can leverage compatibility to strengthen their power across different markets.

Furthermore, the importance of compatibility to consumers can be assessed by examining respondents' second smartphone brand choices in the survey. The survey asks: if your current smartphone was unavailable at the time of purchase, what would have been your second choice? Table 8, 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 further explore the role of compatibility, Table 8, Panel B, provides the probability of choosing the same brand for both first and second smartphone choices, conditional on laptop brand ownership. Conditional on owning an Apple laptop, the probability of choosing an Apple smartphone as both first and sec-

Table 7: Survey results- smartphone brand probability

Panel A: Smartphone brand probability		**Panel B: Smartphone brand probability conditional on laptop brand- Top 8 pairs**			
Brand	Pr(brand)	Smartphone	Laptop	Smartphone-laptop pair share	Pr(smartphone brand | 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

ond choice is 0.95, likely due to Apple's closed ecosystem. This increase in probability, conditional on laptop brand, suggests that owned laptops reveal an important source of unobserved preference heterogeneity.

Table 8: Survey results: Alignment between smartphone first and second brand choices

Panel A: Smartphone brand matching probability		**Panel B: Smartphone brand matching probability conditional on laptop brand - Top 8 pairs**				
		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

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 while owning laptop c, maximizing the following indirect utility function:[10]

$$u_{ij}(x_j, q_{jc}) = \sum_{k=1}^{K} x_{jk}\beta_{ik} + \sum_{g=1}^{G} q_{jcg}\Gamma_{ig} + \lambda_{mj} + \alpha_i p_j + \xi_j + \epsilon_{ij}, \tag{3}$$

where x_{jk} and q_{jcg} are the characteristics of product j that are independent and dependent on ownership of laptop c, respectively.[11] For example, independent product characteristics k include screen size, storage, and speed, while dependent characteristics g include cross-product features such as copy-paste, Camera Continuity, and Handoff. Equation (3) assumes additive separability between x_{jk} and q_{jcg}, as the effect of independent smartphone characteristics x_{jk} on utility does not depend on the dependent characteristics q_{jcg}. λ_{mj} represents the brand fixed effect for product j produced by brand m.

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 et al. (1999), I assume that a consumer's price sensitivity depends on her income and use a first-order linear approximation for $\log(\text{income}_i - \text{price}_j)$, i.e., $\frac{\text{price}_j}{\text{income}_i}$.

ξ_j represents product j's unobservable characteristics, and ϵ_{ij} denotes mean-zero idiosyncratic consumer-product specific terms. β_{ik} and Γ_{ig} are, respectively, individual-

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

[11] Fan and Yang (2020) examines the demand for smartphones as a composite of a device and a carrier contract since they analyzed the market until April 2013. As their paper argues, "In April 2013, T-Mobile launched an 'Uncarrier' campaign, which abandoned service contracts and subsidies for devices. Other carriers followed suit." Although in October 2020, carriers reintroduced long-term contract discounts, all carriers offered to purchase contracts from competitors and provided the same smartphones. Since contracts do not vary in compatibility, the paper examines smartphone demand independently of carrier contracts. Moreover, the surge in Apple's smartphone market share occurred before long-term contracts were reintroduced, reaching 50% at the end of 2019.

specific tastes for independent and dependent cross-market product characteristics k and g, as follows:

$$\begin{aligned}\beta_{ik} &= \beta_k + \sum_r d_{ir}\beta^o_{kr} + \beta^u_k \nu_{ik} \\ \Gamma_{ig} &= \Gamma_g + \sum_r d_{ir}\Gamma^o_{gr} + \Gamma^u_k \nu_{ig},\end{aligned} \tag{4}$$

where β_k and Γ_g are, respectively, individuals' mean taste for dependent and independent product characteristics. $\boldsymbol{d_i}$ 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 (3) and (4), one gets,

$$\begin{aligned}u_{ij}(x_j, q_{jc}) = \delta_j &+ \sum_{kr} x_{jk} d_{ir} \beta^o_{kr} + \sum_k x_{jk}\nu_{ik}\beta^u_k \\ &+ \sum_{gr} q_{jcg} d_{ir}\Gamma^o_{gr} + \sum_g q_{jcg}\nu_{ig}\Gamma^u_g \\ &+ \alpha_i p_j + \epsilon_{ij},\end{aligned} \tag{5}$$

where δ_j is the sum of mean attributes, brand fixed effect and ξ_j,

$$\delta_j = \sum_k x_{jk}\beta_k + \sum_g x_{jcg}\Gamma_g + \lambda_{mj} + \xi_j. \tag{6}$$

In Equation (5), if smartphone j and laptop c are incompatible, i.e., q_{jcg} equals zero, then the second line is eliminated. Thus, one reverts to the classic case of within-market product contingent attributes, i.e., independent of consumers' laptop ownership, that determines utility.

As customary in the literature, I normalize the outside good as follows

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

Following the literature, I make specific assumptions about the underlying distributions. 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, facilitating computation. This results in the familiar logit model for the choice probabilities conditional on $(\mathbf{d}_i, \boldsymbol{\nu}_i)$, as outlined in Equation (7).

$$Pr_{(ij|\mathbf{d}_i,\boldsymbol{\nu}_i,\boldsymbol{\theta},\mathbf{x},\mathbf{q})} = \frac{\exp(\delta_j + \sum_{kr} x_{jk} d_{ir} \beta^o_{kr} + \sum_{k} x_{jk} \nu_{ik} \beta^u_k + \sum_{gr} q_{jcg} d_{ir} \Gamma^o_{gr} + \sum_{g} q_{jcg} \nu_{ig} \Gamma^u_g + \alpha_i p_j)}{1 + \sum_{l} exp(\delta_l + \sum_{kr} x_{lk} d_{ir} \beta^o_{kr} + \sum_{k} x_{lk} \nu_{ik} \beta^u_k + \sum_{gr} q_{lcg} d_{ir} \Gamma^o_{gr} + \sum_{g} q_{lcg} \nu_{ig} \Gamma^u_g + \alpha_i p_j)}. \tag{7}$$

Equation (7) consists of the mean value, δ, the price, and two pairs of observed and unobserved individual specific taste terms: the dependent characteristics, x, and the independent ones, q.

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, 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 shifter, w_j, 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[12]:

$$log(mc_j) = \gamma x_j + \omega_j. \tag{8}$$

Marginal costs and prices are independent of compatibility. Consequently, profit maximization with respect to price—whether accounting for expected consumers in a complementary market or not—leads to identical pricing outcomes in a static model. Firm $f = 1, \ldots, F$ maximizes the following profit function with respect to p_j,

$$\max_{p_j} \pi^f = \sum_{j \in \mathscr{J}^f} [p_j - mc_j] s_j(p) \times M, \tag{9}$$

where $\mathscr{J}^f$ is the set of smartphones produced by firm f, p_j, mc_j, and $s_j(p)$ are the price, marginal cost, and market share of smartphone j, respectively. M represents the size of the smartphone market, as described in Section 3.3.1.

4.3 Open ecosystems forces

Open ecosystems allow consumers to own products with any brand while maintaining connectivity between their smartphones and laptops. Assume that with closed ecosystems, an owned laptop c is compatible with smartphone j but not with $\tilde{j}$, i.e., $q_{jcg} > 0$ and $q_{\tilde{j}cg} = 0$. Once ecosystems are open, smartphone $\tilde{j}$ and laptop c become potentially compatible, where a consumer can utilize connectivity that is the maximum of each product with any other device, i.e., $q_{\tilde{j}c} = \max\{q_{\tilde{j}\cdot}, q_{\cdot c}\}$, where, with abuse of notation, $(\cdot)$ denotes any other smartphone or laptop. For example, since Apple's connectivity is

[12] 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 et al., 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).

higher, consumers who own Apple laptops and purchase Samsung smartphones benefit from compatibility as if they own two Apple products in a closed ecosystem.[13]

Since owning a single device from an ecosystem enables cross-product connectivity, rather than requiring a matched pair of devices, there is greater substitutability between smartphones, increased consumer elasticity, and reduced switching costs when moving between ecosystems, as it results in zero compatibility under closed ecosystems. Open ecosystems transform the compatibility embedded in the owned laptop from a business-stealing effect—where, for example, Apple laptop owners are required to purchase an Apple smartphone for compatibility—into a positive spillover; for instance, consumers who purchase a Samsung smartphone while owning an Apple laptop still benefit from Apple's compatibility level. This shift introduces a competitive displacement effect in the smartphone market.

Open ecosystems can result in a price increase if the surge in demand outweighs the competitive effect of greater substitutability between smartphones. The price increase may diminish the consumer surplus of individuals with a low compatibility coefficient, Γ_{ig}, and higher price sensitivity, α_i. Additionally, since consumers can enjoy compatibility by owning only one product that belongs to an ecosystem before the policy change, the smartphone market may become highly concentrated when a firm offers high compatibility and its independent characteristics x_{jk} (i.e., hardware) are sufficiently higher than others. For example, non-Apple laptop owners may switch to Apple smartphones to benefit from higher connectivity if Apple's hardware characteristics are better than those of competitors.

[13] I assume that with open ecosystems, compatibility is determined by the maximum, rather than the minimum, between any smartphone and laptop in relation to other goods. Using the minimum would reduce the impact of open ecosystems. This is because non-Apple laptop owners would gain no additional compatibility when switching to Apple smartphones, given that non-Apple laptops have a lower compatibility index. Similarly, Apple laptop owners would experience a decline in their compatibility index when transitioning to Samsung smartphones, as Samsung devices exhibit a lower compatibility index. Thus, consumers have less incentive to switch to a smartphone outside their ecosystem.

5 Estimation and Results

The demand and marginal cost estimations mostly follow the approach of Berry et al. (2004), with the key distinction being the identification of compatibility and its interaction with ΔWTP. Identifying the coefficient on individuals' specific tastes for compatibility characteristics, Γ, is derived from variation in pre-owned laptops for a given smartphone.[14]

I estimate the model using GMM, following the best practices outlined by Berry et al. (2004); Conlon and Gortmaker (2020, 2023). Using the microdata from the survey, one can compare sample moments with the moments predicted by the model for different θ's, then choose the θ that minimizes this distance.

Since products' attributes are both dependent and independent of consumers' owned laptops, two types of moments are identified: those independent of owned laptops and those that depend on them. Thus, one can match the following moments: (*i*) the covariance of observed first-choice product attributes, i.e., $\mathbf{x}$ and $\mathbf{q}$, with observed consumer characteristics, i.e., $\mathbf{d}$; (*ii*) the covariance of observed first-choice product attributes, i.e., $\mathbf{x}^1$ and $\mathbf{q}^1$, with the second choice product characteristics, i.e., $\mathbf{x}^2$ and $\mathbf{q}^2$; (*iii*) the market share of products in a market; (*iv*) finally, unique to this paper, one can also optimally utilize the experimental data by constructing a moment that matches the covariance of individuals difference in WTP and product compatibility charactertics, i.e., $Cov(q_{jc} - q_{jc'}, \Delta WTP)$, where q_{jc} and $q_{jc'}$ are compatible and incomptible, respectively.[15] In practice, the estimation matches the observed and estimated first and second choices of Apple products, the change in WTP due to compatibility (or the compatibility choice influenced by a higher ΔWTP), and the market shares.

[14] Identifying β, the tastes for independent product characteristics, relies only on variations in smartphone characteristics from consumers' choices that do not impact compatibility.

[15] Since $q_{jc'} = 0$ due to incompatibility, this is equivalent to

$$Cov(q_{jc}, \Delta WTP) = Cov(q_{j\cdot}, \Delta WTP | q_{\cdot c}) = E(q_{j\cdot} \times \Delta WTP | q_{\cdot c}) - E(q_{j\cdot} | q_{\cdot c}) E(\Delta WTP | q_{\cdot c}).$$

In the experiment, participants who own at least one Apple product exhibit a higher change in WTP due to compatibility. I assume this larger change in WTP by Apple owners is due to their knowledge that Apple products have more compatibility features.

5.1 Results

Table 9 presents the demand and marginal cost estimation results. The results show that consumers value smartphones' dependent and independent characteristics, which is consistent with the experimental outcomes. Consumers value smartphone compatibility with laptops at $322, which is approximately 3.5 times higher than the experiment's results. This difference is attributable to the inclusion of nearly three times more compatibility features in the model and the substantial variation in compatibility between Apple, Samsung, and their competitors. Consumers value an additional 0.1-inch increase in screen size at $15 (similar to Fan and Yang (2020)), a one GHz increase in processor speed at $152, and an additional 10 GB of storage at $10. Apple's fixed effect is the highest at $262, which is expectedly substantially lower than in the literature due to the role of compatibility, followed by Samsung's at $159. The random coefficient on potential compatibility with smartphones is both large and highly significant.

Table 10 presents the price elasticities for the top ten smartphones in 2018. As expected, the diagonal values are negative and large in absolute values, indicating that a one percent change in the price of a smartphone leads to a 2.7-4.2 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 0.26. Most cross-brand elasticities are much lower than those found by Fan and Yang (2020), arguably due to the compatibility effect that ties consumers to ecosystems.

Table 11 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 price, stop purchasing j compared to those who leave j and purchase k instead. Following Conlon and Mortimer (2021), the diagonal represents the diversion to the outside good. As expected, there is a lower diversion ratio to highly differentiated products, such as the iPhone X with XS Max, compared to the iPhone XR. Most of the 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

Table 9: Smartphone estimation results

Variable	Parameter	Standard error
Individual level coefficient		
Price/income	-89.8156	25.9172
Compatibility	3.5956	1.4458
Common coefficient		
Screen size (inches)	1.6693	0.2035
Megapixels	0.0063	0.0033
Storage (GB)	0.0116	0.0018
Processor speed (GHz)	1.6956	0.3996
Processor cores	0.1220	0.0635
Apple	2.9187	0.6106
Samsung	1.7685	0.2105
LG	0.1565	0.2308
Absorb Year FE	Yes	
Random coefficient		
Compatibility product	4.1457	1.3138
Marginal cost ($)		
Screen size	317.2009	0.1138
Megapixels	91.1382	0.3650
Storage	90.6937	0.0062
Processor speed	332.3779	0.0017
Processor cores	113.8479	0.4760
Absorb Year FE	Yes	

Note: Compatibility product is a device's maximum potential connectivity index.

S9+ or Aristo 2 (Motorola), the diversion ratio for the latter can be higher than that for some Apple products due to independent smartphone characteristics. Additionally, the diversion ratio to the outside good is very high for the iPhone XS Max and XS, the most expensive smartphones in the table, arguably because of their distinct, independent features.

Table 10: 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	-3.8079	0.0543	**0.0139**	**0.2685**	0.0000	0.0001	0.0001	0.0004	0.0013	0.0245
iPhone 8	0.2587	-3.5173	0.0159	0.2742	0.0000	0.0002	0.0001	0.0005	0.0015	0.0240
iPhone 8 Plus	0.2608	0.0625	-4.2838	0.2970	0.0000	0.0001	0.0001	0.0005	0.0015	0.0195
iPhone XR	0.2420	0.0519	0.0143	-4.2257	0.0000	0.0001	0.0001	0.0004	0.0013	0.0219
iPhone XS Max	0.0591	0.0203	0.0029	0.0470	-2.7221	0.0064	0.0000	0.0001	0.0004	0.0106
iPhone XS	0.0591	0.0203	0.0029	0.0470	0.0008	-2.7165	0.0000	0.0001	0.0004	0.0106
Galaxy S9	0.2610	0.0636	0.0169	0.2918	0.0000	0.0001	-4.0838	0.0005	0.0015	0.0207
Galaxy S9+	0.2610	0.0632	0.0170	0.2937	0.0000	0.0001	0.0001	-4.1555	0.0015	0.0203
iPhone 7	0.2606	0.0648	0.0165	0.2852	0.0000	0.0002	0.0001	0.0005	-3.8651	0.0221
Aristo 2	0.1664	0.0343	0.0071	0.1649	0.0000	0.0002	0.0000	0.0002	0.0007	-3.4788

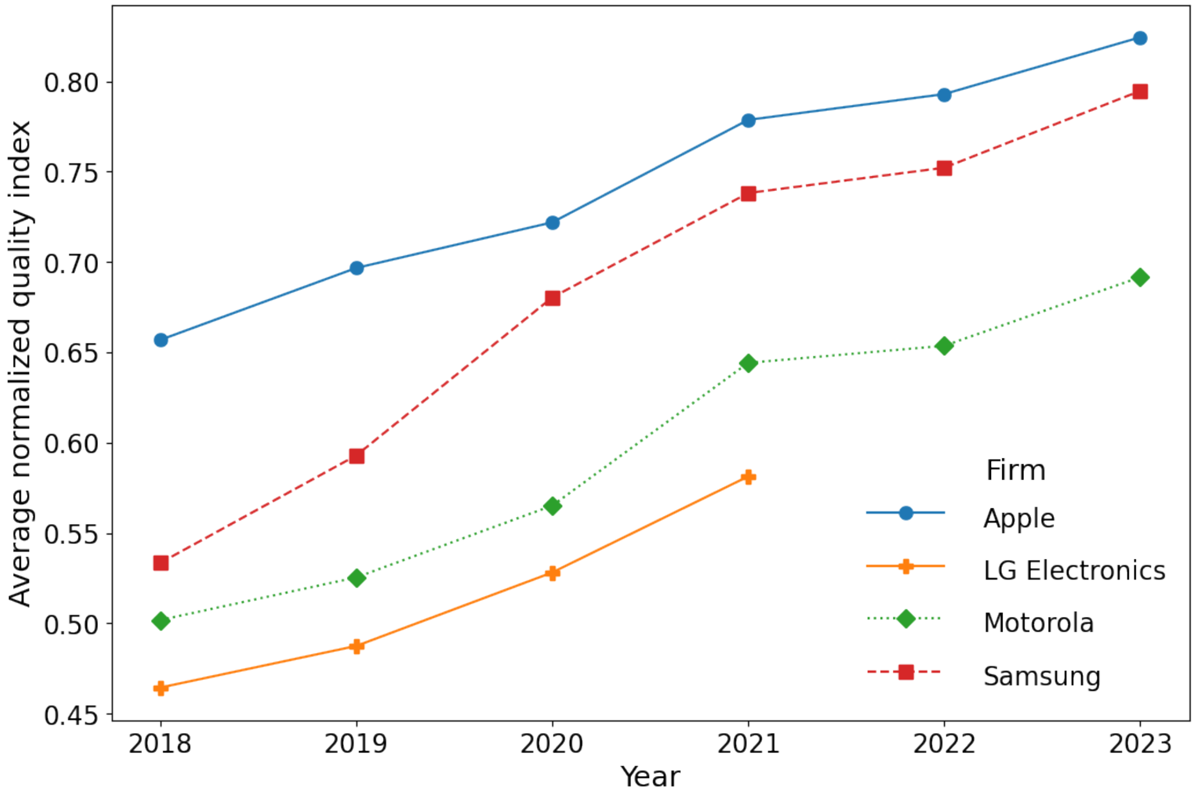
Table 11: Diversion ratio with respect to price- 2018 top 10 products

	iPhone X	iPhone 8	iPhone 8 Plus	iPhone XR	iPhone XS Max	iPhone XS	Galaxy S9	Galaxy S9+	iPhone 7	Aristo 2
iPhone X	0.0031	0.0176	0.0033	0.0596	0.0000	0.0003	0.0000	0.0001	0.0004	0.0091
iPhone 8	0.0597	0.0047	0.0033	0.0535	0.0001	0.0004	0.0000	0.0001	0.0004	0.0078
iPhone 8 Plus	0.0679	0.0201	0.0026	0.0654	0.0000	0.0003	0.0000	0.0001	0.0004	0.0072
iPhone XR	0.0678	0.0179	0.0036	0.0022	0.0000	0.0002	0.0000	0.0001	0.0004	0.0087
iPhone XS Max	0.0026	0.0011	0.0001	0.0017	0.4562	0.0024	0.0000	0.0000	0.0000	0.0007
iPhone XS	0.0026	0.0011	0.0001	0.0017	0.0003	0.4572	0.0000	0.0000	0.0000	0.0007
Galaxy S9	0.0654	0.0196	0.0038	0.0618	0.0000	0.0003	0.0031	0.0001	0.0004	0.0073
Galaxy S9+	0.0662	0.0198	0.0039	0.0629	0.0000	0.0003	0.0000	0.0029	0.0004	0.0073
iPhone 7	0.0627	0.0192	0.0036	0.0580	0.0000	0.0003	0.0000	0.0001	0.0037	0.0075
Aristo 2	0.0338	0.0086	0.0013	0.0283	0.0000	0.0003	0.0000	0.0000	0.0002	0.0033

Figure 2 depicts smartphones' average normalized hardware quality (i.e., x_j in Equation (3)) 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.

Opening ecosystems may attract consumers tied to Samsung smartphones under closed ecosystems to switch to Apple due to higher compatibility when Apple's hardware quality is substantially better (i.e., differences in x_j in Equation (3)), as observed in 2018 and 2019. However, the low mean hardware quality gap starting in 2020 may encourage consumers previously tied to Apple to switch to Samsung, as certain Samsung

Figure 2: Smartphone average hardware quality by year



smartphones surpass Apple in hardware quality while retaining compatibility.

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

Open ecosystems enable consumers to benefit from cross-product compatibility while purchasing previously incompatible devices. I define product pairs as potentially compatible, with compatibility determined by their highest connectivity to any other product in closed ecosystems (see subsection 4.3 for details). I then solve for the equilibrium prices and market shares for smartphones and calculate both consumer and producer surplus.

Table 12 shows the average effect of open ecosystem across firms for each year from 2018 to 2023. The results reveal that, on average, the inside good share increases by 4.5%, prices decrease by $27, and consumer surplus rises by $15.5 billion. Open ecosystems increase product substitutability and, thus, competition, leading to lower prices and greater surplus for all consumers, including those with low compatibility values. The profit effect varies across years but is mostly negative, as Apple's losses outweigh competitors' gains. This is due to Apple's cross-market power in closed ecosystems, where Apple laptop owners are tied to Apple smartphones for compatibility (with survey data showing an Apple smartphone purchase probability of 0.82, conditional on owning Apple laptops). In open ecosystems, this tie is broken, increasing smartphone substitutability, as Apple laptop owners experience similar compatibility when choosing between Apple and Samsung smartphones.

Table 13 presents the annual average impact of open ecosystems on firms. Apple's profit declines while competitors' profits rise, as expected, due to increased smartphone substitutability, as consumers are no longer tied to ecosystems for compatibility. Apple's average price reduction is about five times greater than that of its competitors, with

Table 12: Open ecosystems- average effect across firms

Market	ΔInside good share	ΔSmartphone price	ΔFirms profit	ΔCS
2018	0.0204	-17.88	451.59	15,887.06
2019	0.0317	-3.17	-209.64	13,475.32
2020	0.0438	-47.13	-1,894.63	13,586.23
2021	0.0313	-33.59	-1,086.38	14,706.60
2022	0.0738	-27.01	151.39	17,659.74
2023	0.0787	-33.11	-189.81	17,549.62

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

a mean decrease of $64. 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.

Table 13: Open ecosystems- average firm effect across years

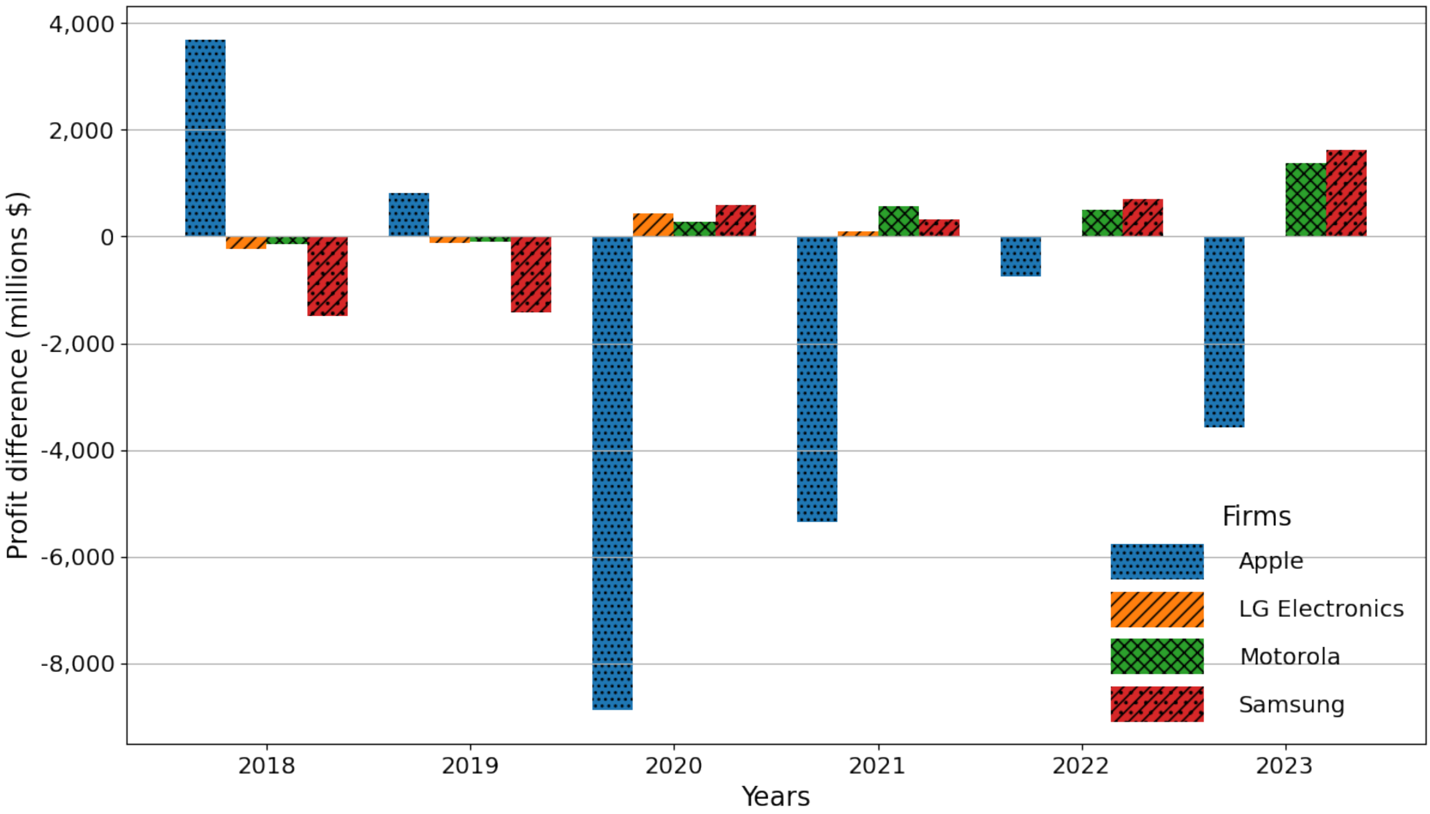
Firm	ΔInside good share	ΔSmartphone price	ΔFirms profit	ΔCS
Apple	0.0287	-64.27	-2,345.40	3,209.03
LG	0.0229	-13.76	43.99	7,804.03
Motorola	0.0497	-10.23	416.11	7,496.95
Samsung	0.0674	-14.23	54.71	9,487.43

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

Figure 3 illustrates the annual changes in firms' profits. In the first two years, Apple's profits rise while those of its competitors decline, but this trend reverses in the following four years. The most substantial price reductions for Apple occur during these later periods, as consumers switch away from Apple products, i.e., low price sensitivity. This shift explains Apple's relatively low contribution to consumer surplus despite the significant price drop, leading to a decrease in Apple's profit.

To understand the varying effects of open ecosystems on profit across different periods, I examine smartphones' average normalized hardware quality, as depicted in Figure 2.

Figure 3: Open ecosystems effect on firms profit by year



The average hardware quality gap between Apple and Samsung in the first two years is substantial. This causes consumers previously tied to Samsung's ecosystem to switch to Apple to benefit from higher compatibility and hardware quality, resulting in increased profit for Apple and higher market concentration.

However, between 2020 and 2023, the average hardware quality gap between Apple and Samsung is inconsiderable, where some of Samsung's devices suppress Apple's. During this period, consumers who own Apple laptops shift toward purchasing Samsung smartphones, as they can still benefit from high compatibility without a significant loss, and sometimes gain, in hardware quality (recall Figure 2 depicts the mean hardware quality). This results in a profit loss for Apple, an increase in its competitors, and a fall in market concentration. The relatively low change in firms' profits in 2022 is due to a lower share of Apple laptops among consumers participating in the market that year.

To conclude, the hardware quality dimension largely affects the impact of open ecosystems on firms' profits. When the quality gap between Apple and Samsung is substantial, Apple's profit increases, as does market concentration. Conversely, when the quality gap is low, Apple's profit decreases while competitors' profits increase, leading to a decrease in market concentration.

Opening ecosystems increases consumer surplus, suggesting that regulators should mandate open ecosystems. However, regulators might be concerned about Apple's increased market power when the hardware quality gap is significant. To address this, regulators could condition the policy on the hardware quality gap, ensuring that market concentration does not increase.

6.1.1 Comaptibility license

In recent years, regulators have increasingly forced firms to license their products and patents so that consumers can benefit from these licensed features when purchasing competitors' products. For example, in 2020, the Federal Trade Commission filed a lawsuit against Qualcomm for anti-competitive practices, forcing it to "commit to license their SEPs (standard essential patents) on fair, reasonable, and nondiscriminatory ('FRAND') terms before their patents are incorporated into standards."[16] Therefore, I briefly acknowledge the results of compatibility licensing as an alternative to forcing firms to open their ecosystems.

Licensing Apple's compatibility allows consumers to connect smartphones to any laptop with Apple's compatibility level, regardless of owning even one Apple product. This is different from open ecosystems that require at least one Apple product to benefit from its compatibility level. When Apple licenses compatibility with only Samsung or all competitors, Apple's profit decreases more than its competitors' increases. This occurs due to Apple's near-monopolistic power over consumers who benefit from its compatibility before the licensing. Consequently, no contract exists under which Apple agrees to license its compatibility solely to Samsung or to all its competitors.

[16] For more, see `https://cdn.ca9.uscourts.gov/datastore/opinions/2020/08/11/19-16122.pdf`

6.2 Cross-market merger

Existing antitrust policies scrutinize cross-market mergers of technology firms without considering the causal effect of compatibility on demand. As a result, they may fail to address the impact of these mergers.

I examine the effect of a cross-market merger between Samsung, which, despite manufacturing in the laptop market, has a share of only 3%, and HP, which has the highest share in the laptop market. The cross-market merger provides consumers who own Samsung or HP laptops with maximum compatibility with Samsung smartphones. I solve for the new equilibrium prices and market shares and calculate consumer and producer surplus.

Table 14 provides the annual effect of the Samsung-HP merger across firms. The results show that, on average, there is a negligible increase in inside good shares, while Apple's shares decrease substantially. Additionally, the merger has varying effects on prices and profits. The positive changes in prices and profits can be attributed to the relative increase in Samsung's compatibility and the hardware quality gap. Before the merger, until 2020, Samsung's compatibility is less common. Therefore, the merger, which enhances the merged entity's compatibility, has a greater impact in the first three years, leading to a higher price and profit increase for Samsung compared to the final three years. Despite years of price increases, the average effect on consumer surplus remains positive.

Table 14: Samsung-HP merger - average effect across firms

Market	ΔInside good share	ΔApple share	ΔSmartphone price	ΔFirms profit	ΔCS
2018	0.0079	0.0041	36.76	793.61	5,950.51
2019	0.0086	-0.1210	51.75	1,296.50	4,060.86
2020	0.0005	-0.0783	82.96	2,793.38	2,255.05
2021	0.0070	-0.0461	-10.61	-985.07	3,440.91
2022	0.0175	-0.0257	-27.86	-1,579.11	4,686.55
2023	0.0233	-0.0317	-15.85	-965.60	3,803.96

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

Table 15 provides the effect of the Samsung-HP merger on firms across years. On average, Samsung's market share increases by 11% while Apple's decreases by 5%, 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 $179 and its profit by $11 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 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.

Table 15: Samsung-HP merger- average firm effect across years

Firm	ΔInside good share	ΔSmartphone Price	ΔFrims profit	ΔCS
Apple	-0.0498	-84.50	-9,140.05	981.66
LG	-0.0163	-4.90	-305.67	2,414.21
Motorola	-0.0176	-6.16	-342.23	1,923.38
Samsung	0.1146	179.31	11,012.64	2,164.45

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

I examine the merged entity's decision on whether to maintain its previous, lower level of compatibility with Windows laptop competitors. The analysis finds that the merged entity is indifferent to whether to maintain low or incompatibility with non-Apple laptop brands. This indifference is due to Samsung's superior average hardware quality compared to non-Apple smartphones, which sustains demand even with incompatibility.

To conclude, the Samsung-HP cross-market merger increases average consumer surplus, though its effects are heterogeneous. Consumers with low compatibility value who purchase Samsung products may be worse off due to higher prices, while others benefit from either lower prices or enhanced compatibility. The merger reduces market concentration by expanding Samsung's share while decreasing Apple's. Therefore, the regulator should consider approving the merger in the smartphone-laptop markets. Current antitrust policies, which have largely overlooked the role of compatibility, fail to account for the full effects of cross-market mergers.

7 Conclusion

Antitrust policies have traditionally focused on competition within markets or on add-on products across markets. However, ostensibly independent stand-alone products may be interconnected through ecosystems, which can amplify firms' market power. This market power is not easily mitigated by within-market competition alone: although hardware quality may be matched, firms can maintain dominance by restricting access to their ecosystems.

Using experimental settings, I demonstrate that smartphone demand rises as a causal result of cross-product compatibility with laptops. This study then provides an empirical framework to quantify the impact of cross-product compatibility on market power within a static competition model. Through open ecosystem and cross-market merger counterfactuals, I highlight compatibility's critical role in shaping market power. The main takeaways are: *(i)* open ecosystems significantly influence market concentration in the smartphone industry, with the extent of this impact contingent on the hardware quality gap between firms. *(ii)* Cross-market mergers between smartphone and laptop firms, often overlooked in antitrust policy, can substantially decrease market concentration in the smartphone market by enhancing compatibility across products.

More broadly, this paper advances the methodology for identifying causal relationships within experimental settings and extends the literature examining the effects of open ecosystems and cross-market mergers on consumer and firm welfare. It emphasizes that stand-alone products, unlike add-ons, require distinct analytical tools to capture their unique impact on competition. These insights are especially valuable for researchers and policymakers focused on antitrust policies, as they reveal critical dynamics in how ecosystems across stand-alone products influence market competition and firm dominance.

The analysis makes a few assumptions. First, while one can conclude from the survey that consumers are myopic and thus demand is non-dynamic, the paper assumes the supply is static. Although marginal costs and prices are independent of compatibility, yielding the same results when conditioning on expected consumers in a complementary market within a period, firms may still be forward-looking. Since the model incorporates a large variety of products, consumer heterogeneity via random coefficients and product characteristics, and an endogenous product portfolio, using a dynamic supply model is beyond the scope of this paper. Therefore, I follow the endogenous product choice literature (Eizenberg, 2014; Berry et al., 2016; Crawford et al., 2019; Fan and Yang, 2020) by assuming a static supply.

Second, the paper assumes that firms keep their product characteristics unchanged in response to open ecosystems and mergers. Since incompatibility ties consumers to ecosystems, firms in closed ecosystems may delay introducing independent product characteristics that would otherwise differentiate them from competitors. For example, while brands like Samsung and Motorola introduce "foldable" smartphone screens in 2020, Apple has not yet introduced this feature. Thus, open ecosystems may encourage firms to enhance independent product quality. However, open ecosystems may reduce firms' incentives to introduce dependent product characteristics. I examine the effect of open ecosystems on investment and product choice in a separate paper.

Third, the compatibility index weighs all features equally, while consumers may value them differently. Since each compatibility feature adds 636 columns to the agent data (one for each product) and firms have introduced compatibility features in bulks, I assume consumers value compatibility features as an index rather than considering each one independently.

Further research quantifying the effects of cross-market power and compatibility is essential to inform the broader debate on whether regulators should mandate open ecosystems and allow cross-market mergers. Due to limitations in the quality of available data on the laptop market, this paper focuses exclusively on the smartphone market, conditional on owned laptops, without analyzing the laptop market given owned smartphones. Future studies should explore various technology markets and assess the positive spillover effects of compatibility against the potential negative impacts of cross-market power.

References

G. M. Allenby, N. Hardt, and P. E. Rossi. Economic foundations of conjoint analysis. In *Handbook of the Economics of Marketing*, volume 1, pages 151–192. Elsevier, 2019.

A. Arora, J. P. Caulkins, and R. Telang. Research note—sell first, fix later: Impact of patching on software quality. *Management Science*, 52(3):465–471, 2006.

G. M. Becker, M. H. DeGroot, and J. Marschak. Measuring utility by a single-response sequential method. *Behavioral science*, 9(3):226–232, 1964.

J. Berry, G. Fischer, and R. Guiteras. Eliciting and utilizing willingness to pay: Evidence from field trials in northern ghana. *Journal of Political Economy*, 128(4):1436–1473, 2020.

S. Berry, J. Levinsohn, and A. Pakes. Automobile prices in market equilibrium. *Econometrica*, 63(4):841–890, 1995. ISSN 00129682, 14680262. URL `http://www.jstor.org/stable/2171802`.

S. Berry, J. Levinsohn, and A. Pakes. Voluntary export restraints on automobiles: Evaluating a trade policy. *American Economic Review*, 89(3):400–431, 1999.

S. Berry, J. Levinsohn, and A. Pakes. Differentiated products demand systems from a combination of micro and macro data: The new car market. *Journal of political Economy*, 112(1):68–105, 2004.

S. Berry, A. Eizenberg, and J. Waldfogel. Optimal product variety in radio markets. *The RAND Journal of Economics*, 47(3):463–497, 2016.

L. Coffman and P. Niehaus. Pathways of persuasion. *Games and Economic Behavior*, 124:239–253, 2020.

C. Conlon and J. Gortmaker. Best practices for differentiated products demand estimation with pyblp. *The RAND Journal of Economics*, 51(4):1108–1161, 2020.

C. Conlon and J. Gortmaker. Incorporating micro data into differentiated products demand estimation with pyblp. Technical report, National Bureau of Economic Research, 2023.

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

G. S. Crawford, O. Shcherbakov, and M. Shum. Quality overprovision in cable television markets. *American Economic Review*, 109(3):956–995, 2019.

K. De Corte, J. Cairns, and R. Grieve. Stated versus revealed preferences: An approach to reduce bias. *Health economics*, 30(5):1095–1123, 2021.

A. Eizenberg. Upstream innovation and product variety in the us home pc market. *Review of Economic Studies*, 81(3):1003–1045, 2014.

G. Ellison and D. Fudenberg. The neo-luddite's lament: Excessive upgrades in the software industry. *The RAND Journal of Economics*, pages 253–272, 2000.

D. Ershov, J.-W. Laliberté, and S. Orr. Mergers in a model with complementarity. *Scott, Mergers in a Model with Complementarity (December 3, 2018)*, 2018.

D. Ershov, J.-W. Laliberté, M. Marcoux, and S. Orr. Estimating complementarity with large choice sets: An application to mergers. *Mathieu and Orr, Scott, Estimating Complementarity With Large Choice Sets: An Application to Mergers (March 10, 2021)*, 2021.

C. L. Exley and K. Nielsen. The gender gap in confidence: Expected but not accounted for. *American Economic Review*, 114(3):851–885, 2024.

P. Eyal, R. David, G. Andrew, E. Zak, and D. Ekaterina. Data quality of platforms and panels for online behavioral research. *Behavior research methods*, pages 1–20, 2021.

Y. Fan and C. Yang. Competition, product proliferation, and welfare: A study of the us smartphone market. *American Economic Journal: Microeconomics*, 12(2):99–134, 2020.

J. Farrell and P. Klemperer. Coordination and lock-in: Competition with switching costs and network effects. *Handbook of industrial organization*, 3:1967–2072, 2007.

C. Grebitus, J. L. Lusk, and R. M. Nayga Jr. Explaining differences in real and hypothetical experimental auctions and choice experiments with personality. *Journal of Economic Psychology*, 36:11–26, 2013.

J. J. Heckman. Causal parameters and policy analysis in economics: A twentieth century retrospective. *The Quarterly Journal of Economics*, 115(1):45–97, 2000.

Y. Huang. Tied goods and consumer switching costs. *Marketing Science*, 41(1):93–114, 2022.

R. S. Lee. Vertical integration and exclusivity in platform and two-sided markets. *American Economic Review*, 103(7):2960–3000, 2013.

J. Li. Compatibility and investment in the us electric vehicle market. *Unpublished manuscript, MIT*, 2023.

C. Matutes and P. Regibeau. " mix and match": product compatibility without network externalities. *The RAND Journal of Economics*, pages 221–234, 1988.

F. B. Norwood, J. L. Lusk, and T. Boyer. 26 forecasting hypothetical bias. *Environmental economics, experimental methods*, 10:447, 2007.

A. Pakes. A helicopter tour of some underlying issues in empirical industrial organization. *Annual Review of Economics*, 13:397–421, 2021.

A. Pakes, J. R. Porter, M. Shepard, and S. Calder-Wang. Unobserved heterogeneity, state dependence, and health plan choices. Technical report, National Bureau of Economic Research, 2021.

S. Palan and C. Schitter. Prolific. ac—a subject pool for online experiments. *Journal of Behavioral and Experimental Finance*, 17:22–27, 2018.

M. Song, S. Nicholson, and C. Lucarelli. Mergers with interfirm bundling: a case of pharmaceutical cocktails. *The RAND Journal of Economics*, 48(3):810–834, 2017.

S. Stantcheva. How to run surveys: A guide to creating your own identifying variation and revealing the invisible. *Annual Review of Economics*, 15:205–234, 2023.

A. Wang. A blp demand model of product-level market shares with complementarity. *Available at SSRN 3785148*, 2021.

T. G. Wollmann. Trucks without bailouts: Equilibrium product characteristics for commercial vehicles. *American Economic Review*, 108(6):1364–1406, 2018.

Appendix A: WTP

Table 16: 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 17: 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***

Appendix B: 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 18. 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.

Table 18: Panel A: 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