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

Yuval Lidany§

Abstract

This paper examines the role of compatibility across *standalone* technology products in anchoring consumers to ecosystems. Through a novel experimental design that elicits willingness to pay for a smartphone both before and after a laptop is gifted to the participant, I identify the causal impact of compatibility: smartphone valuations increase by 11% more when the randomly gifted laptop is compatible. I use the experimental results to estimate a model of smartphone demand that incorporates compatibility with laptops. I quantify the effects of regulations requiring cross-brand compatibility (i.e., "open ecosystems") and cross-market mergers. Open ecosystem counterfactual reveals that in 2018-2019, smartphone market concentration rises as non-Apple laptop owners switch to Apple smartphones due to Apple's superior hardware quality and compatibility. However, in 2020-2023, when the hardware gap narrows, market concentration decreases as Apple laptop owners opt for Samsung devices. In both cases, consumer surplus increases due to lower prices and a wider variety of compatible products. Counterfactual merger between Samsung and HP, Apple's main smartphone and laptop rivals, respectively, reduces smartphone market concentration but leads to higher prices set by the merged entity due to its cross-market power. The higher prices have a heterogeneous impact on consumer surplus, with those valuing compatibility less being worse off.

*I am indebted for the advice and mentorship of Charles Murry and Lucas Coffman. I thank Michael Grubb, Richard Sweeney, Arthur Lewbel, Uzi Segal, Mariana Laverde, James Anderson, Rodrigo Valdenegro, Alon Eizenberg, and seminar participants at the Hebrew University for their valuable comments. All errors are my own.

§Boston College, lidany@bc.edu.

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

(Steve Jobs, former Apple CEO).

1 Introduction

The compatibility of *standalone* technology products, such as smartphones, laptops, and smartwatches, has yet to be explored in the literature but holds significant potential to influence consumer demand and exacerbate market power. For example, consumers seeking compatibility features like seamless copy-paste functionality across devices would need to buy Apple smartphones if they already own Apple laptops, and Samsung owners would need Android devices.

Should regulators mandate open ecosystems when firms produce non-substitute standalone technology products such as smartphones and laptops? This question gains prominence as the Department of Justice (DOJ) filed a lawsuit against Apple in March 2024 for tethering consumers to its ecosystem. Open ecosystems allow consumers to benefit from compatibility features without being locked into a single platform, thereby increasing the variety of compatible products, reducing switching costs, and enhancing consumer elasticity and surplus (Farrell and Klemperer, 2007). However, open ecosystems may also lead to higher prices due to a greater expansion in demand than in competition, which reduces surplus for consumers who value compatibility less (Matutes and Regibeau, 1988). Additionally, open ecosystems could increase smartphone market concentration by enabling non-Apple laptop users to purchase Apple smartphones while benefiting from connectivity, potentially amplifying Apple's market dominance.

Additionally, regulators may need to keep compatibility in mind when evaluating mergers, prompting the question: What is the welfare effect of a cross-market merger? Although the DOJ's 2014 report on Lenovo's acquisition of Motorola does not account for compatibility, this factor is increasingly significant in today's markets. Cross-market mergers can enhance compatibility and eliminate double marginalization by boosting demand in complementary markets (Song et al., 2017; Ershov et al., 2018). However, the

merged firm may leverage cross-market power to raise prices and opt for incompatibility with competitors, reducing product variety and consumer surplus.

Collecting unique data, I evaluate the impact of compatibility on smartphone demand and competition in five steps. First, I establish the causal effect of compatibility on demand within an experimental framework, where participants offer prices for smartphones before and after potentially being gifted a laptop. The change in smartphone willingness to pay (WTP) when the laptop is of the same brand identifies the causal impact of compatibility. Second, I construct a demand model where smartphone purchase decisions are conditioned on existing laptop ownership, based on survey data. In this model, prices are set in a static Nash-Bertrand equilibrium. Third, I estimate the model using repeated cross-sectional market data from the International Data Corporation's (IDC) Tracker spanning 2018-2024, alongside a proprietary compatibility index, survey responses, and a unique micro-moment that matches the change in WTP measured in the experiment with compatibility.[1] Fourth, I assess the implications of a counterfactual scenario that allows for the interoperability of firms' ecosystems. Fifth, I analyze the effects of a counterfactual merger across the smartphone and laptop markets.

The experiment and survey I conduct serve three crucial purposes. First, since typical product data is cross-sectional, it does not inherently link the smartphone and laptop markets. Thus, revealing consumers' ownership patterns is essential to connect these markets. Second, the experiment provides a direct measurement of WTP for compatibility. Third, the survey allows for the construction of four key components essential to the demand model: *(i)* Estimating the smartphone market size by dividing the U.S. population over 15 years old by the average acquisition frequency, leveraging purchase recurrence data; *(ii)* Demonstrating that agents participate in one market at a time; *(iii)* Finding that consumers are myopic when purchasing devices rather than considering future costs of a laptop; *(iv)* Utilizing the relationships between consumers' purchasing behaviors and demographic attributes to employ a non-parametric distribution.

The experiment results reveal that compatibility significantly impacts demand. Con-

[1] Eizenberg (2014) employs IDC data.

sistent with the literature, merely stated preference yields higher WTP than the payment mechanism (List and Gallet, 2001), justifying the novel experimental approach. When participants are unaware of compatibility, the change in the average WTP for compatible smartphones is an insignificant $7. Given that smartphones are durable and expensive goods typically researched by consumers, and the experiment uses a random pool that may be uninformed, I provide participants with compatibility information. When participants are aware of compatibility features, the average change in WTP is a significant $88.

Consequently, I design a structural model that incorporates compatibility features. This model accounts for the influence of owned laptops on the characteristics of smartphones offered for purchase, enabling evaluation of how compatibility affects consumers' purchase decisions. I estimate the model of smartphone demand and find that consumers place significant value on hardware and compatibility characteristics.

I evaluate the welfare implications of an open ecosystem 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, open ecosystems drive consumers previously loyal to Samsung's ecosystem to switch to Apple smartphones because of higher compatibility. This shift increases market concentration and boosts Apple's profits while negatively impacting its competitors. However, from 2020 to 2023, as the hardware quality gap narrows, Apple laptop owners opt for Samsung smartphones, as compatibility remains constant and Samsung's top devices exceed Apple's in hardware quality. In both cases, 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 market share at the expense of Apple, resulting in lower market concentration. Although the merger raises the mean consumer surplus, the rise in the merged entity's

prices reduces the surplus for those who value compatibility less. The merged entity remains indifferent to incompatibility with non-HP laptops, as Samsung's superior average hardware quality compared to non-Apple smartphones sustains demand.

This paper contributes to four branches of the literature. First, it adds to the growing empirical research on opening closed ecosystems. Ex-ante, the impact of compatibility is ambiguous: it may broaden the variety of compatible products and reduce switching costs, but it can also lead to higher prices, reducing surplus for consumers who value compatibility less, and increasing market concentration (Lee, 2013; Huang, 2022; Li, 2023). While previous studies focus on the incompatibility of add-on products, which results in zero utility and exclusion from consumers' consideration sets, *incompatible standalone* goods can still provide positive value, where connectivity influences product attributes. This inconspicuous influence on consumer decisions highlights the need to examine compatibility's impact on standalone technological products. I extend the literature by *(i)* revealing ecosystems' impact on demand for standalone products, previously attributed to brand preference and loyalty, *(ii)* examining non-singleton compatibility that affects product attributes, and *(iii)* demonstrating the role of the owned laptop, which in the literature is considered unobservable, in shaping the characteristics of an offered-to-purchase smartphone.[2]

Second, this paper enhances the quantitative understanding of cross-market mergers when products can be consumed independently and together. The impact of smartphone and laptop firm mergers is theoretically ambiguous: on the one hand, a merger might incentivize the merged firm to lower prices and enhance compatibility to capture demand across complementary markets; on the other hand, it could reduce consumer surplus due to increased market power (Song et al., 2017; Ershov et al., 2021; Wang, 2021). This study extends previous empirical research by examining the effects of cross-market mergers of standalone products in the technology sector—an area that, to my knowledge, has not previously been explored. Current antitrust policies are oblivious to the role of

[2]For more on distinguishing unobserved heterogeneity from state-dependent preferences, see, for example, Pakes et al. (2021). This paper designs a choice model with state dependence that allows for unobserved heterogeneity of individual-good fixed effects, which is used to analyze the persistence of health insurance plan choices without accounting for the mechanism generating the state dependence.

compatibility, thus ineffective for cross-market mergers of technology firms. Furthermore, by analyzing the compatibility decisions of the merged firm with 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 the smartphone and laptop markets. Eizenberg (2014) examines the impact of rapid CPU innovation on product variety in the personal computer market, while Fan and Yang (2020) investigates the variety and merger effects in 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 may affect firms' cost structures, hence influencing product variety estimation. Additionally, by demonstrating the demand dependency, the paper shows how firms may exacerbate power across markets.

Fourth, this paper aligns with the growing trend of using experimental designs to identify deep parameters in structural models (see Cohen et al. (2020) for measuring time preferences and Heckman (2000) for causal analysis). Pakes (2021), in an overview of 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 our framework, merely observing smartphone and laptop purchases is insufficient to determine whether consumers buy these devices due to causal cross-product compatibility or mere correlation. One might suspect a correlation, given that compatibility is costless to consumers and the literature provides no evidence of connectivity binding consumers to stand-alone products.

Since conflating causality with correlation can lead to costly errors, i.e., maintaining closed ecosystems and deterring cross-market mergers, this paper identifies causality by exogenously varying the object of interest—in this case, cross-product compatibility—using an experimental design. The experiment measures agents' WTP for a smartphone given a laptop and a monetary lottery prize that agents can win. By altering the brand of the laptop prize, the design generates smartphone-laptop pairs with varying

degrees of compatibility. This exogenous variation allows us to observe how changes in device compatibility affect agents' WTP for a smartphone, thereby establishing a causal relationship. While Ershov et al. (2021) attempts to distinguish between correlation and causality, their work provides only spatially suggestive evidence of suppliers' joint pricing strategies. Additionally, this paper advances the literature by uniquely leveraging experimental data; within the structural model, it constructs a moment that matches the covariance between individual changes in WTP and product compatibility characteristics, providing a robust analysis of the causal impact of cross-product compatibility.

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- deep parameter causality

Consumers often purchase and use smartphones and laptops as standalone devices, which might suggest that their ownership is merely correlated. However, product compatibility can influence purchasing decisions, turning what appears to be a correlation into a causative effect stemming from the compatibility between devices.

To examine whether compatibility impacts demand for stand-alone goods and estimate participants' valuation of compatibility, I design an experiment that randomly gives away laptops and then elicits how this changes the WTP for smartphones due to compatibility by varying the laptop brands.

2.1 Consumer decision

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

$$u_{i(j,c)} = V_{ij} + W_{i(j,c)} - P_{i(j,c)} \tag{1}$$

where V and W are, respectively, the value from smartphone j characterstics that is independent and dependent of laptop c. $P_{i(j,c)}$ is the price that consumer i is willing to pay for smartphone j when owns laptop c, which may be equal to $P_{i(j,\cdot)}$. Equation (1) assumes that V and W are additively separable, as conditioning on hardware characteristics V reveals significant variation in compatibility characteristics W.

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:

$$\begin{aligned} u_{i(j,c)} &\geq u_{i(j,c')} \\ W_{i(j,c)} - P_{i(j,c)} &\geq -P_{i(j,c')} \\ W_{i(j,c)} &\geq P_{i(j,c)} - P_{i(j,c')} \end{aligned}$$

where the second inequality comes from incompatibility of smartphone j and laptop c', i.e., $W_{i(j,c')} = 0$. Note that $P_{i(j,c)} - P_{i(j,c')}$ is consumer i willingness to pay for compatibility, i.e., net of product characteristics that are independent of laptops. Thus, if $P_{i(j,c)} - P_{i(j,c')} > 0$, consumer i values compatibility. I therefore examine the difference in consumers' willingness to pay for smartphone j when it is compatible with laptop c and incompatible with c'.

2.2 Experiment design

To establish a baseline WTP for smartphones and to examine the importance of owned laptops, the experiment first asks participants for their WTP for Apple and Samsung smartphones without a laptop lottery. Participants who value compatibility can change their WTPs depending on the connectivity with their laptops. However, since participants' owned laptops are not randomly assigned, this introduces a confounding state. Therefore, I next randomized agent-owned product sets by introducing a lottery for a laptop and a cash prize. Only a lottery winner can purchase a product (depending on their WTP, as explained hereafter), ensuring independence between previously owned laptops and the WTP for an offered-to-purchase smartphone.

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 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 the laptop and the \$RP; otherwise, the winner acquires the laptop, smartphone, and a cash payment equal to the difference between the smartphone's RP and the randomly drawn price, i.e., *laptop + smartphone + (\$RP - \$p)*. Participants see identical WTP questions, with the elicitation order randomized.

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

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 the offered-to-purchase 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, par-

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

ticipants 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 products are chosen to have the same prices; Apple and Samsung laptops are priced at $999, and smartphones at $799. Therefore, varying the laptop lottery prize while offering to purchase the same smartphone only results in a change in 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 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, and automatically connect to a smartphone hotspot from a laptop.

To control for participants' prior knowledge, the experiment asks whether they knew about connectivity characteristics beforehand. Finally, the experiment examines whether and to what extent asking for participants' offers without providing compatibility attributes anchors the following WTPs with connectivity information. To examine the anchoring effect, the experiment randomly assigns a small sample to observe the compatibility information immediately without first providing their WTP in the absence of compatibility information.

The low probability of winning the lottery prize does not affect the experiment results. Since each question has an equal chance of being drawn, the low probability does not differently influence questions with compatible and incompatible products or with and without connectivity information. Therefore, changes in agents' WTP are solely explained

by compatibility.

Before starting the WTP elicitation, participants are asked whether they are eligible for discounts when purchasing devices. This allows control over unexplained WTP variation due to retail price differences. For example, Apple offers a $150 discount for students purchasing a computer. Additionally, to eradicate participants' concerns about switching costs, including moving across ecosystems, participants are informed that professional support will be 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 change in WTP within individual participants and across different participants when the offered smartphone is compatible or incompatible with the awarded laptop.

2.4 Recruitment

Subject recruitment is done using the online platform Prolific, which provides a diverse and heterogeneous sample of the U.S. population and is increasingly used in social science in general, particularly in experimental economics (Palan and Schitter, 2018; Eyal et al., 2021). I randomly recruited 1,000 agents who previously completed at least a thousand tasks on Prolific.[4] 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 than the 2022 mean Current Population Survey (CPS).

The experiment takes 20 minutes on average, and participants are paid a base rate

[4]Due to the platform's data recording error, the analysis could only use 992 participants. The results are insensitive to this.

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			

Table 1: Demographic descriptive statistics

of 4$ and prizes they can win. This pool of agents and an additional 118 (62 males and 56 females) respondents not participating in the experiment serve us for the survey 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 mechanism. This supports the need for the experiment design to elicit participants' true WTP.

As seen in Table 2, without providing participants with compatibility information, the change in WTP between compatible and incompatible smartphones for those who report they do not know (group "✗") about connectivity is $9 for Apple and $6 for Samsung smartphones, where the difference is only significant for Apple. I define the higher WTP for smartphones by the same laptop brand without compatibility pre-knowledge as a *"brand matching fixed effect,"* which is captured as part of the brand fixed effect in the literature. The change in WTP between compatible and incompatible smartphones for those who report they know about connectivity is $17 for Apple and $18 for Samsung, where these differences are significant. If participants' "know" state reports conveyed

the full knowledge about compatibility features, providing participants with connectivity information should not affect the WTP; however, as I present next, this is not the case.

Smartphone brand	Compatibility pre-knowledge	N	Mean WTP compatibility	Mean WTP incompatibility	Mean difference
Apple	✗	263	413.92 (241.95)	405.01 (243.72)	8.90*
Samsung	✗	363	393.87 (239.87)	387.86 (244.05)	6.00
Apple	✓	630	504.96 (226.59)	487.43 (228.33)	17.52***
Samsung	✓	530	489.80 (214.59)	471.79 (218.59)	18.01***

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

Table 2: WTP without compatibility information

The WTP for compatible and incompatible smartphones conditional on connectivity information provision is presented in Table 3. Participants' WTPs for compatible Apple and Samsung smartphones are, respectively, \$96 and \$79, significantly higher than for incompatible devices. Net of the "brand matching fixed effect," participants' WTPs for Apple and Samsung connectivity features are \$87 and \$73, respectively. Nonetheless, the increase in the WTP difference with compatibility information can be driven either by participants' surprise about those characteristics or by participants who reported that they already knew about connectivity features but may not have considered the full information provided by the experiment. I further examine the source of the increase in the change in WTP in Table 4.

Table 4 presents the WTP with compatibility information provided to participants, controlling for participants' pre-knowledge state. Both groups exhibit an increase in their change in WTP compared to no information provided, as seen in Table 2. Conditional on a smartphone brand, those who report they know about connectivity beforehand (group "✓") have higher smartphone WTPs. Therefore, while the percentage change in WTP

Smartphone brand	Information provided	N	Mean WTP compatibility	Mean WTP incompatibility	Mean difference
Apple	✗	893	478.15 (234.78)	463.16 (235.84)	14.98***
Samsung	✗	893	450.80 (229.96)	437.67 (232.83)	13.13***
Apple	✓	992	495.00 (228.19)	398.55 (222.46)	96.44***
Samsung	✓	992	463.34 (225.17)	383.70 (224.46)	79.64***

Note: Information provided ✗ and ✓ indicate participants answering WTP questions when they are not and are informed about compatibility features, respectively. Standard deviations are in parentheses. Statistical significance is denoted as: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 3: WTP with and without compatibility information

across both groups is similar, those with compatibility pre-knowledge exhibit a greater absolute change 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 change in WTP with information across knowledge states for a given brand reveals that the differences are significant for Apple but not for Samsung.

Smartphone brand	Compatibility pre-knowledge	N	Mean WTP compatibility	Mean WTP incompatibility	Mean difference
Apple	✗	263	431.84 (238.61)	356.49 (222.87)	75.34***
Samsung	✗	363	416.67 (233.98)	341.89 (232.35)	74.77***
Apple	✓	630	521.07 (219.59)	415.80 (220.17)	105.27***
Samsung	✓	530	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: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 4: WTP with information conditional on pre-knowledge state

To further investigate the source of the absolute difference-in-difference in WTP for Apple smartphones in Table 4, I examine participants' product ownership. The analysis reveals that participants who own an Apple product make higher offers for Apple smartphones, indicating selection auxiliary effects beyond treatment. 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 change in WTP for Apple higher.

Comparing Table 3 and 4, one can observe that conditional on compatibility knowledge status reports, when information is provided, the WTPs are higher for compatible smartphones and lower for incompatible devices than without informing about connectivity features. Thus, compatibility increases participants' product valuations for compatible products and decreases them for incompatible ones.

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

One might worry that subjects would feel they should increase their WTP after receiving compatibility information since each bit is good news. If this is true, we should observe a high WTP that does not reflect their true preferences after offering them three pieces of information. To test for this, the experiment randomly assigns participants into two groups: one that sees WTP questions without and then with compatibility information, and one that only observes with information.

Table 5 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 change in participants' WTP for compatible and incompatible Apple smartphones is almost identical across the two groups, \$96. The change 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. Together with participants' monetary incentives to offer their true smartphone values, the lack of anchoring effect supports the conclusion that participants' WTP is attributed to connectivity features rather than the experiment design that "encourages" participants to offer higher prices for compatible products by introducing them to additional product characteristics in a second stage.

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

Table 5: WTP condition on information group

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-to-purchase 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 are unaware of product compatibility, their average WTP for a smartphone from the same brand as their owned laptop is an insignificant \$7. However, when participants are informed about compatibility features, the average change in WTP is a significant \$88. 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' change 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)* IDC's Tracker Database, *(ii)* a survey I conducted, and *(iii)* collected information on product compatibility. 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 a 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 congruity with complementary laptops

3.1 Compatibility Index

Seamless cross-market connectivity across devices begins in October 2013 when Apple introduces "AirDrop," allowing consumers to transfer files across different 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, this paper limits its attention to pre-installed congruity features. I include the following compatibility features: copy-paste, auto hotspot, phone call, text, handoff, file transfer, camera and webcam continuity, and continuity sketch.[5]

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.

[5]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 2024. Average shares in the smartphone and laptop markets are presented in Tables 6 and 7. 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.

The annual mean smartphone sale is 123 million units, with a standard deviation of 11 million units. The maximum sales in our 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 8 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.

Brand	Share
HP	0.31
Apple	0.27
Lenovo	0.17
Dell	0.10
Acer	0.08
ASUS	0.07

Table 6: Laptop average shares 2018-2024

Brand	Share
Apple	0.50
Samsung	0.27
Motorola	0.08
LG	0.07
Alcatel	0.04
Google	0.03
TCL	0.02

Table 7: Smartphone average shares 2018-2024

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		

Table 8: Smartphones characteristics- summary statistics

3.3 Survey

I survey smartphone and laptop product ownership in the U.S. until 2024 by following Allenby et al. (2019); Stantcheva (2023) best practice. In addition to agents participating in the experiment, I survey 119 subjects, where the demographic characteristics of the entire sample are presented in section 3.3.1. The survey provides information on participants' brand, model/series, and purchasing year of current and last smartphones and laptops.[6] Following the literature, I collect series-level data for smartphone brands with numerous models and on laptops (see, for instance, Eizenberg (2014)). For example, in 2022, Samsung launched 52 smartphone models under five different series. For current products, the survey further collects consumers' second-best choice, which is used to construct a micro-moment. Since compatibility is generally determined by series-year combination rather than depending on hardware differences between models, observing series and year is sufficient.

3.3.1 Rewighting survey data

The IDC repeated cross-section data represents the U.S. smartphone and laptop markets. Since the study connects the cross-section data by surveying product ownership across

[6]If participants are uncertain about their current smartphone information, they are offered to check brand, model, and purchasing year-month using their serial number online, e.g., `https://iunlocker.com/`.

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 2018-2024 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 9 and 10. Overall, 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.

	Mean		
	Initial	Reweight	CPS
Age	39.94	42.34	43.44
	(10.26)	(13.59)	(13.42)
Income	$59,837.80	$52,409.33	$52,945.03
	(42,540.92)	(44,178.67)	(44,241.33)
Education	15.01	14.05	14.03
	(2.20)	(2.44)	(2.46)
Gender	1.44	1.50	1.52
	(0.51)	(0.50)	(0.50)

Table 9: Reweighted demographic

	Share		
Brand	Initial	Reweight	IDC
hp	0.1966	0.30	0.31
Apple	0.1791	0.27	0.27
Lenovo	0.1215	0.16	0.17
Dell	0.1867	0.10	0.10
Acer	0.0641	0.08	0.08
Asus	0.0817	0.07	0.07

Table 10: Reweighted owned laptop

3.3.2 Samrtphone and laptop 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, assuming that 17% of the population owns more than one device to account for the discrepancy between the estimated market size and observed sales.

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.[7] Therefore, I construct a static model in which consumers' decisions depend on ownership of a complementary good without being forward-looking.

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

3.4 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.

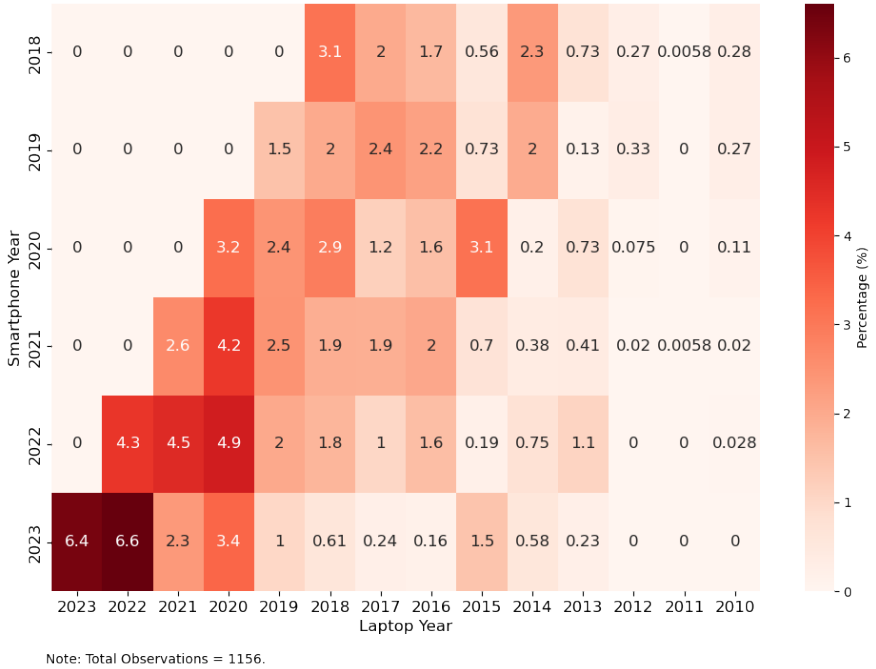


Figure 1: Smartphone conditional distribution

Examining agents' brand choices in the survey further underscores the importance of product compatibility for consumers and its effect on market power. Table 11 provides the probability of consumers choosing a smartphone brand, while Table 12 shows the probability conditional on laptop ownership. In Table 11, the average probability of purchasing an Apple smartphone between 2018 and 2024 is 0.50, the highest in the market. However, conditional on owning an Apple laptop, the probability of purchasing an Apple smartphone in Table 12 increases by 62% to 0.82, further solidifying Apple's position as the market leader. Given Apple's closed ecosystem, this significant increase in purchasing probability highlights the importance of compatibility to consumers. Additionally, this

increase in purchase probability demonstrates how firms can leverage compatibility to strengthen their power across different markets.

Brand	Pr(brand)
Apple	0.50
Samsung	0.27
Motorola	0.08
LG	0.05
Google	0.03

Table 11: Survey results- smartphone brand probability

Smartphone	Laptop	Smartphone-laptop pair share	Pr(smartphone brand | laptop brand)
Apple	Apple	**0.22**	**0.82**
Apple	hp	0.13	0.42
Samsung	hp	0.11	0.38
Apple	Lenovo	0.07	0.41
Motorola	hp	0.04	0.13
Samsung	asus	0.04	0.54
Samsung	Lenovo	0.04	0.22
Samsung	dell	0.03	0.33

Table 12: Survey results- smartphone brand probability conditional on laptop brand

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 13 shows that consumers who initially chose Apple or Samsung have probabilities of 0.75 and 0.46, respectively, of selecting the same brand as their second smartphone choice. To further explore the role of compatibility, Table 14 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 second choice is 0.94, 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.

Smartphone Brand	Pr(2nd = 1st brand choice)
Apple	0.75
Google	0.42
LG	0.40
Motorola	0.23
Samsung	0.47

Table 13: Survey results- probability of smartphone second brand choice similar to first brand choice

Laptop brand	Smartphone			
	Apple	Samsung	Motorola	Google
Acer	0.47	0.39	0.08	0.01
Apple	**0.95**	0.04	0.00	0.00
Asus	0.41	0.36	0.04	0.01
Dell	0.52	0.40	0.02	0.01
hp	0.53	0.37	0.08	0.00
Lenovo	0.54	0.23	0.00	0.12
Microsoft	0.34	0.61	0.00	0.01
Samsung	0.70	0.30	0.00	0.00

Table 14: Survey results- probability of smartphone second brand choice similar to first brand choice conditional on laptop brand

4 Model

I employ a random-coefficient discrete choice model that incorporates the effect of a consumer-specific state laptop on smartphone compatibility characteristics to describe demand.

4.1 Demand

Assume a smartphone (S) market that consists of t periods. Consumer i purchases smartphone j while owning laptop c, maximizing the following indirect utility:

$$u_{ij}(x_j, q_{(j,c)}) = \sum_{k=1}^{K} x_{jk}\beta_{ik} + \sum_{g=1}^{G} q_{(j,c)g}\Gamma_{ig} + \xi_j + \epsilon_{ij} \tag{3}$$

where x_{jk} and $q_{(j,c)g}$ are the characteristics of product j that are independent and dependent on ownership of laptop c, respectively.[8] For example, independent product characteristics are screen size, storage, and speed, while dependent ones are cross-product copy-paste, Camera Continuity, and Handoff. Equation (3) assumes that x_{jk} and $q_{(j,c)g}$ are additively separable, as conditioning on hardware characteristics x_{jk} demonstrates significant variation in compatibility characteristics $q_{(j,c)g}$.

Since bundling discounts are rare in the smartphone and laptop markets and consumers usually buy products at different times, α_i may vary with demographic characteristics, whereas p does not. I thus simplify the notation by assuming the price is part of x. 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-specific tastes for independent and dependent cross-market product characteristics k and g, as follows:

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

where $\boldsymbol{d_i}$ 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. Since compatibility characteristics inherently depend on a consumer's owned laptop, Γ_{ig} includes only consumer-dependent terms without a constant.

[8] 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.

Consumers' attributes include demographics (e.g., income and sex) and ownership of laptops.

Combining Equations (3) and (4), one gets,

$$\begin{aligned} u_{ij}(x_j, q_{(j,c)}) = \delta_j &+ \sum_{kr} x_{jk} d_{ir} \beta^o_{kr} + \sum_{k} x_{jk} \nu_{ik} \beta^u_k \\ &+ \sum_{gr} q_{(j,c)g} d_{ir} \Gamma^o_{gr} + \sum_{g} q_{(j,c)g} \nu_{ig} \Gamma^u_g \\ &+ \epsilon_{ij} \end{aligned} \tag{5}$$

where δ_j is the sum of mean attributes and ξ_j

$$\delta_j = \sum_k x_{jk} \beta_k + \xi_j \tag{6}$$

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

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

$$U_{it0} = \epsilon_{it0}$$

Following the literature, the paper makes subsequent assumptions on the distributions. I assume a parametric distribution for (ν, ϵ), a non-parametric distribution for observed consumer attributes $\boldsymbol{d}$ from the reweighted survey, and that ξ_j is mean independent of non-price product attributes. Using BLP-type instruments together with exchange rates from Japan, South Korea, and China to eliminate the simultaneity problem of prices, one can estimate $\theta = (\delta, \beta^o, \beta^u, \Gamma^o, \Gamma^u)$ using the micro-data.

Let $\mathbf{D}$ be the observed $(\mathbf{d}_i)$ and unobserved $(\boldsymbol{\nu}_i, \boldsymbol{\epsilon}_i)$ individual attributes vector, where its distribution in the population is $P_{\mathbf{D}}$. One finds the share of consumers who choose product j by integrating over the set of consumers' attributes for which individuals choose good j.

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 observed product's cost shifter, w_j, which are assumed to be the same as the product's observed characteristics, x_j, and on unobserved ω_j, as follows[9]:

$$log(mc_j) = \gamma x_j + \omega_j \tag{7}$$

Firm f^d maximizes the following profit function with respect to p_j,

$$\max_{p_j} \pi^d = \sum_{j \in \mathscr{J}^d} \big[p_j - mc_j\big] s_j(p) \times M \tag{8}$$

where $\mathscr{J}^d$ represents the configurations that firm f^d produces. p_j, mc_j, and $s_j(p)$ are, respectively, the price, marginal cost, and market share of configuration j. M is the size of the smartphone market, estimated from the survey by dividing the U.S. population over 15 years old by the average frequency at which agents purchase products.

4.3 Opened ecosystems forces

I identify the forces in the model. Opened ecosystems allow consumers to own products by any brand while maintaining connectivity between smartphones and laptops. Assume that with closed ecosystems, an owned laptop c is compatible with smarpthone j but not with $\tilde{j}$, i.e., $q_{(j,c)g} > 0$ and $q_{(\tilde{j},c)g} = 0$. Once ecosystems are opened, smartphone $\tilde{j}$ and laptop c are potentially compatible, where their connectivity is the maximum of each product with any other device, i.e., $q_{(\tilde{j},c)} = \max\{q_{(\tilde{j},\cdot)}, q_{(\cdot,c)}\}$. For example, since

[9]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).

Apple's connectivity is higher, consumers who own Apple laptops and purchase Samsung smartphones benefit from compatibility as if they own two Apple products with closed ecosystems.

Since owning a device belonging to an ecosystem rather than a pair is sufficient for cross-product connectivity, there is higher substitutability between smartphones, increased consumer elasticity, and eliminated switching costs associated with moving across ecosystems. This shifts the compatibility embedded in the owned laptop from business stealing toward a positive spillover effect while also having a competitive displacement effect in the offered-to-purchase smartphone market.

The opened ecosystem can increase prices when competition expands less than demand. The price increase may diminish consumer surplus among individuals with a lower compatibility coefficient, Γ_{ig}, and higher price sensitivity, α_{ig}. Additionally, since consumers can enjoy compatibility by owning only one product that belongs to an ecosystem before the policy change, the market may become highly concentrated when a firm offers high compatibility and its independent characteristics (i.e., hardware) are sufficiently higher than others. For example, non-Apple laptop owners may switch to Apple smartphones to benefit from higher connectivity when Apple's hardware characteristics are better than those of competitors.

5 Estimation and Results

The identification relies on variations in consumers' smartphone choices and pre-owned laptops. Identifying the coefficient on individuals' specific taste for compatibility characteristics, Γ, is derived from a smartphone choice given a variation in a pre-owned laptop. Identifying β, the tastes for independent product characteristics, relies only on variations in smartphone characteristics from consumers' choices that do not impact compatibility.

I estimate the model using GMM, following Berry et al. (2004); Conlon and Gortmaker (2020, 2023) best practice. 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 dependent and independent of consumers' owned products, there can be two types of moments. 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, we also optimally utilizing the experimental data by constructing moment that matches the covariance of individuals change in WTP and product compatibility charactertics, i.e., $Cov(q_{(j,c)} - q_{(j,c')}, \Delta WTP)$, where $q_{(j,c)}$ and $q_{(j,c')}$ are compatible and incomptible, respectively.[10] In practice, the estimation matches the observed and estimated first and second choice of Apple products, the change in WTP due to compatibility, and the market shares.

Specifying unobserved distributions, one can derive the model prediction. Let $(\boldsymbol{\nu}_i, \boldsymbol{\epsilon}_i)$ be distributed independently of $\mathbf{d}_i$ and each other, the non-price deviation from the mean ν are independent normal, and the unobserved interacted with the price is lognormal to avoid a preference for higher prices. As conventional in the literature, assume the idiosyncratic error ϵ_{ij} are independently and identically distributed Type-I extreme value to ease computation. This results in the familiar logit model choice probability conditional on $(\mathbf{d}_i, \boldsymbol{\nu}_i)$ in Equation (9),

$$Pr_{(ij|\mathbf{d}_i,\boldsymbol{\nu}_i,\boldsymbol{\theta},\mathbf{x},\mathbf{q})} = \frac{\exp(\delta_j + \sum_{kr} x_{jk} d_{ir} \beta^o_{kr} + \sum_k x_{jk} \nu_{ik} \beta^u_k + \sum_{gr} q_{(j,c)g} d_{ir} \Gamma^o_{gr} + \sum_g q_{(j,c)g} \nu_{ig} \Gamma^u_g)}{1 + \sum_l exp(\delta_l + \sum_{kr} x_{lk} d_{ir} \beta^o_{kr} + \sum_k x_{lk} \nu_{ik} \beta^u_k + \sum_{gr} q_{(l,c)g} d_{ir} \Gamma^o_{gr} + \sum_g q_{(l,c)g} \nu_{ig} \Gamma^u_g)}. \tag{9}$$

Equation (9) consists of the mean value, δ, and two pairs of observed and unobserved individual specific taste terms: the dependent characteristics, x, and the independent

[10] Since $q_{(j,c')} = 0$ due to incompatibility, this is equivalent to

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

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.

ones, q.

5.1 Results

Table 15 provides the demand and marginal cost estimation results. The results show that consumers value smartphones' dependent and independent characteristics. Consumers value smartphone compatibility with laptops at \$322, which is arround three times higher than the experiment result of \$88 due to the inclusion of three times more compatibility features and the high 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 lower than in the literature due to the role of compatibility, followed by Samsung's at \$159.

Table 16 presents the price elasticities for the top ten smartphones in 2018. As expected, the diagonal values are negative and large in absolute terms, 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 0.25. 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 17 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

Variable	Parameter	Standard error
Individual level coefficient		
Price/income	-89.8156	25.9172
Connectivity	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
Year dummy	Yes	
Random coefficient		
Connect 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
Year dummy	Yes	

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

Table 15: Smartphone estimation results

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.

	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 16: 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	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

Table 17: Diversion ratio with respect to price- 2018 top 10 products

Figure 2 depicts smartphones' average normalized hardware quality between 2018 and 2024. 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 to switch to Apple when there is a high-quality gap, such as in 2018 and 2019. However, the low mean hardware quality gap can encourage consumers who have previously been tied to Apple to switch to Samsung, as some Samsung devices surpass Apple's hardware quality.

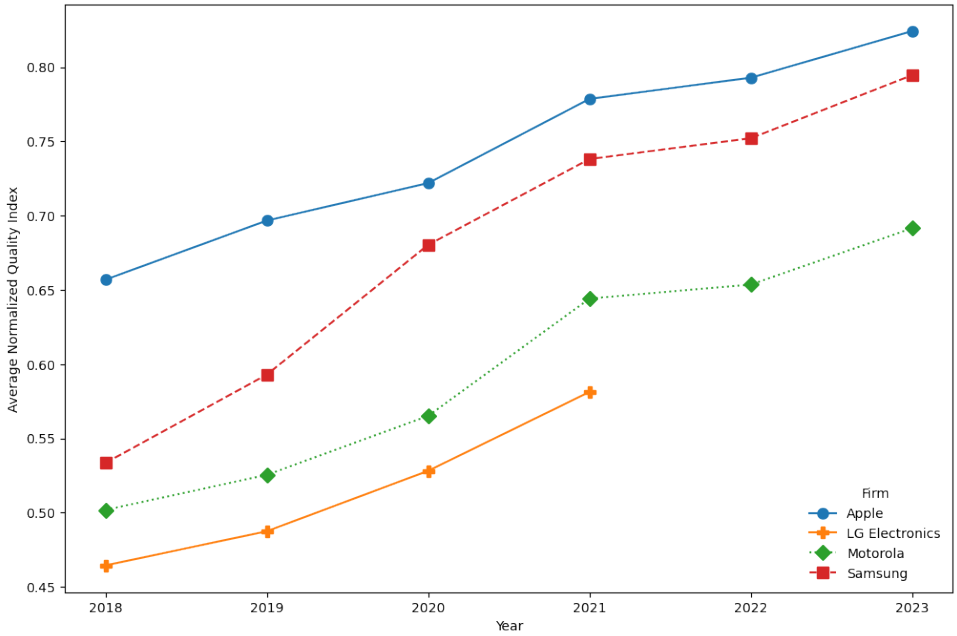


Figure 2: Smartphone average hardware quality by year

6 Counterfactual

This section utilizes the estimated parameters to conduct counterfactual simulations for opened ecosystems and the Samsung-HP cross-market merger. These counterfactual analyses enable us to assess the significance of cross-good compatibility in determining welfare outcomes.

6.1 Opened ecosystems welfare effect

Opened ecosystems enable consumers to benefit from compatibility while purchasing previously incompatible products. I define any pair of products as potentially compatible, with compatibility determined by the highest connectivity of each device with any other product when ecosystems are closed (for details, see subsection 4.3). I then solve for the new prices and shares equilibrium and calculate consumer and producer surplus.

Table 18 provides the annual average effect of opened ecosystems across firms. 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 effect on profit varies across years but is mostly negative due to Apple's losses outweighing the profit increases of its competitors. This is explained by Apple's cross-market power, which ties Apple laptop owners to purchase Apple smartphones to benefit from compatibility, with the conditional probability reaching 0.82 under closed ecosystems.

Market	ΔShare	ΔPrice	ΔProfit	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: Profit and CS are in millions.

Table 18: Opened ecosystems- average effect across firms

Table 19 shows the annual average impact of opened ecosystems on firms. While Apple's profit declines, its competitors' profits rise as expected. The average price reduction for Apple is about five times greater than that of its competitors, with a mean decrease of $64. Despite this significant price drop, Apple's contribution to the change in consumer surplus remains the lowest. This is attributed to varying substitution patterns over different periods. To illustrate this, I examine the change in firms' annual profits and prices.

Firm	ΔShare	ΔPrice	ΔProfit	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: Profit and CS are in millions.

Table 19: Opened ecosystems- average firm effect across years

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.

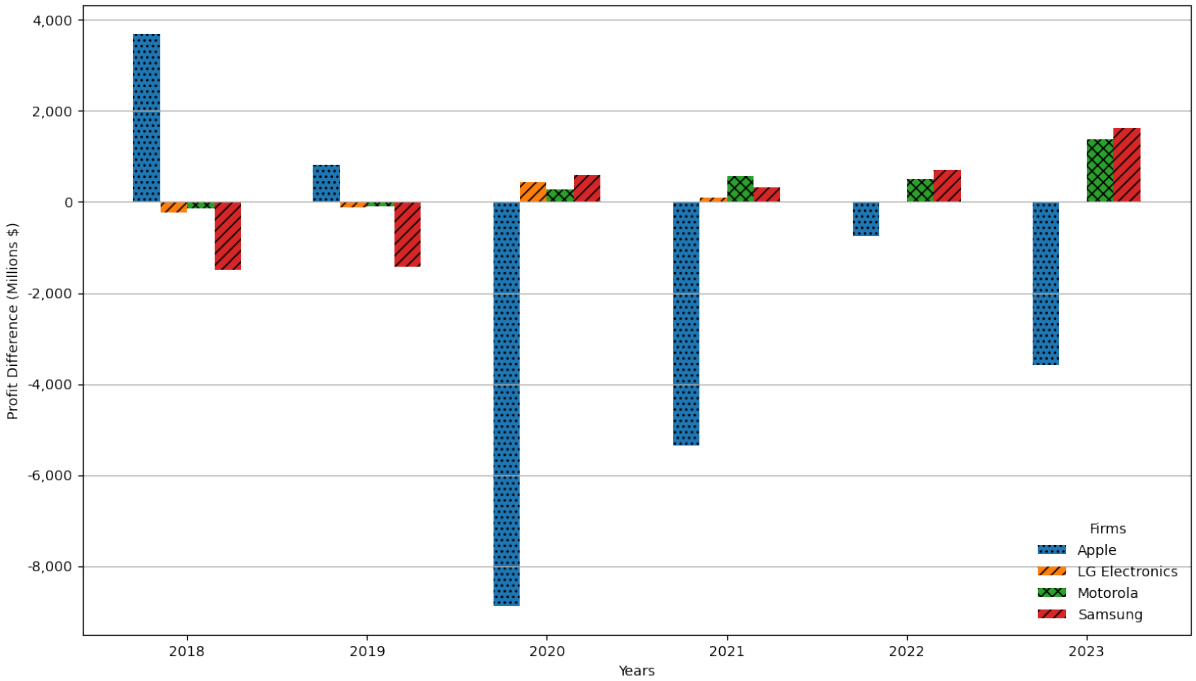


Figure 3: Smartphone firm profit by year

To understand the varying effects of opened ecosystems on profit across different periods, I examine smartphones' average normalized hardware quality, as depicted in Figure 2. 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 2024, 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 opened 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. 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."[11] Therefore, I briefly acknowledge the results of compatibility licensing as an alternative to forcing firms to open their ecosystems.

Licensing Apple's compatibility allows a firm to connect its smartphone to any laptop with Apple's 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. Therefore, no contract exists under which Apple agrees to license its compatibility with competitors.

[11] 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. Therefore, they are ineffective in addressing the true 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 prices and shares equilibrium and calculate consumer and producer surplus.

Table 20 provides the annual average effect of the Samsung-HP merger across firms. The results show that, on average, there is a negligible increase in inside good shares, with varying effects on prices and profits. The positive changes in prices and profits are explained by the relative increase in Samsung's compatibility and the hardware quality gap. Before the merger, until 2020, Samsung compatibility is less common; thus, the merger, which enhances the merged entity's compatibility, has a greater impact in the first three years, resulting in a higher price and profit increase for Samsung than the final three years. The average effect on consumer surplus is positive despite years of price increases.

Market	ΔShare	ΔPrice	ΔProfit	ΔCS
2018	0.0079	36.76	793.61	5,950.51
2019	0.0086	51.75	1,296.50	4,060.86
2020	0.0005	82.96	2,793.38	2,255.05
2021	0.0070	-10.61	-985.07	3,440.91
2022	0.0175	-27.86	-1,579.11	4,686.55
2023	0.0233	-15.85	-965.60	3,803.96

Note: Profit and CS are in millions.

Table 20: Samsung-HP merger- average effect across firms

Table 21 provides the average effect of the Samsung-HP cross-market 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.

Firm	ΔShare	ΔPrice	ΔProfit	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: Profit and CS are in millions.

Table 21: Samsung-HP merger- average firm effect across years

I examine the merged entity's decision on whether to maintain the previous, lower level of compatibility with competitors in the laptop market. The analysis finds that the merged entity is indifferent to whether to maintain low or incompatibility with non-HP 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 the average consumer surplus, but its effect is heterogeneous. Those with low compatibility value who purchase Samsung are worse off due to higher prices, while others benefit from lower prices or higher

compatibility. The merger decreases market concentration by increasing Samsung's share and decreasing Apple's. Therefore, the regulator should approve the cross-market merger in the smartphone-laptop markets.

7 Conclusion

Antitrust policies traditionally focus on within-market competition and add-on products across markets. However, ostensibly independent stand-alone products may be interconnected through ecosystems, which can exacerbate firms' market power. This market power cannot be alleviated through within-market competition alone, as hardware quality can be matched, but firms can restrict ecosystem access to maintain dominance.

This study investigates the role of compatibility between smartphones and laptops in shaping market outcomes. To elucidate the effect of compatibility on competition, the paper first establishes the causal impact of compatibility on demand using experimental settings. The results indicate that, on average, participants are willing to pay $88 for Apple's compatibility features and $74 for Samsung's. This finding is consistent regardless of participants' prior knowledge of compatibility and initially observing WTP without compatibility information.

Building on the findings that compatibility and demand have a causal relationship, this paper develops and estimates a model that incorporates the effect of owned goods on the characteristics of offered-to-purchase products. The model allows us to examine the impact of compatibility on exacerbating market power and welfare.

I simulate the effect of open ecosystems on welfare. The findings show that when the average hardware quality gap between Apple and Samsung is considerable, opening ecosystems increases market concentration and Apple's profit while harming competitors and vice versa. Consumer welfare rises due to lower prices and enhanced cross-product compatibility. This suggests that regulators should mandate firms to open their ecosystems, where this can be conditioned on the hardware quality gap to avoid increasing market concentration. Additionally, I simulate compatibility licensing as an alternative.

The simulation indicates that there is no feasible contract-to-license compatibility, as licensing decreases Apple's profit more than it increases competitors' profits.

The study further contributes to the literature by examining the role of compatibility in cross-market mergers, which antitrust policies have so far been oblivious to. The Samsung-HP merger decreases market concentration but raises the merged entity's prices due to cross-market power, while competitors' prices decrease. In a scenario where consumers who own HP laptops and, before the merger, purchase Apple smartphones place zero value on compatibility, Apple's prices would not decrease, which may prompt regulators to block the merger. Although the average consumer surplus increases, the merger has a heterogeneous effect on consumer welfare, with those having low compatibility value being worse off.

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 firms keep their product characteristics unchanged in response to opened ecosystems and mergers. Since incompatibility ties consumers to ecosystems, firms may postpone introducing independent product characteristics that would otherwise differentiate them from competitors. For example, while brands such as Samsung and Motorola introduce "foldable" smartphone screens in 2020, Apple has not yet introduced this feature. Thus, opened ecosystems may spur firms to increase independent product quality. However, open ecosystems may reduce firms' incentives to introduce dependent product characteristics. I examine the effect of opened 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.

More research quantifying cross-market power and compatibility effects is essential to inform the broader debate about whether regulators should prohibit closed ecosystems and allow cross-market mergers. Future studies should investigate various technology markets and weigh the positive spillover effects between these markets against the adverse impact of cross-market power.

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Appendix A: WTP

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 22: WTP: State-gender, no 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***

Table 23: WTP: Gender, info