

DISCUSSION PAPER SERIES

DP11423

**COMPETITION, PRODUCT
PROLIFERATION AND WELFARE: A
STUDY OF THE U.S. SMARTPHONE
MARKET**

Ying Fan and Chenyu Yang

INDUSTRIAL ORGANIZATION



COMPETITION, PRODUCT PROLIFERATION AND WELFARE: A STUDY OF THE U.S. SMARTPHONE MARKET

Ying Fan and Chenyu Yang

Discussion Paper 11423
Published 01 August 2016
Submitted 01 August 2016

Centre for Economic Policy Research
33 Great Sutton Street, London EC1V 0DX, UK
Tel: +44 (0)20 7183 8801
www.cepr.org

This Discussion Paper is issued under the auspices of the Centre's research programme in **INDUSTRIAL ORGANIZATION**. Any opinions expressed here are those of the author(s) and not those of the Centre for Economic Policy Research. Research disseminated by CEPR may include views on policy, but the Centre itself takes no institutional policy positions.

The Centre for Economic Policy Research was established in 1983 as an educational charity, to promote independent analysis and public discussion of open economies and the relations among them. It is pluralist and non-partisan, bringing economic research to bear on the analysis of medium- and long-run policy questions.

These Discussion Papers often represent preliminary or incomplete work, circulated to encourage discussion and comment. Citation and use of such a paper should take account of its provisional character.

Copyright: Ying Fan and Chenyu Yang

COMPETITION, PRODUCT PROLIFERATION AND WELFARE: A STUDY OF THE U.S. SMARTPHONE MARKET

Abstract

This paper studies (1) whether, from a welfare point of view, oligopolistic competition leads to too few or too many products in a market, and (2) how a change in competition affects the number and the composition of product offerings. We address these two questions in the context of the U.S. smartphone market. Our findings show the market contains too few products and that a reduction in competition decreases both product number and product variety. These results suggest that merger policies should be stricter when we take into account the effects of a merger on product choice in addition to those on pricing.

JEL Classification: L13, L15, L41, L63

Keywords: endogenous product choice, product proliferation, merger, smartphone industry

Ying Fan - yingfan@umich.edu
University of Michigan and CEPR

Chenyu Yang - chny.yang@gmail.com
University of Rochester

Competition, Product Proliferation and Welfare: A Study of the U.S. Smartphone Market*

Ying Fan[†]

University of Michigan and CEPR

Chenyu Yang[‡]

University of Rochester

July 23, 2016

[Click Here for the Latest Version](#)

Abstract

This paper studies (1) whether, from a welfare point of view, oligopolistic competition leads to too few or too many products in a market, and (2) how a change in competition affects the number and the composition of product offerings. We address these two questions in the context of the U.S. smartphone market. Our findings show the market contains too few products and that a reduction in competition decreases both product number and product variety. These results suggest that merger policies should be stricter when we take into account the effects of a merger on product choice in addition to those on pricing.

Key words: endogenous product choice, product proliferation, merger, smartphone industry

JEL Classifications: L13, L15, L41, L63

1 Introduction

In many markets such as the printer market, the CPU market and the smartphone market, firms typically offer multiple products across a wide spectrum of quality. In these markets, product proliferation is an outcome of firms' oligopolistic competition in product space. Does such competition result in too few or too many products from a welfare point of view? How does a change in

*We thank participants at the Barcelona GSE Summer Forum, CEPR/JIE Applied IO conference, Econometric Society North American Summer Meeting, International Industrial Organization Conference, NBER Summer Institute IO Workshop, and World Congress of the Econometric Society, and participants at a seminar at the University of British Columbia for their constructive comments. We thank the Michigan Institute for Teaching and Research in Economics, the NET Institute and Rackham Graduate School of the University of Michigan for their generous financial support.

[†]Department of Economics, University of Michigan, 611 Tappan Street, Ann Arbor, MI 48109; yingfan@umich.edu.

[‡]William E. Simon School of Business Administration, University of Rochester, Rochester, NY 14627; chny.yang@gmail.com.

competition affect the number and composition of product offerings? In this paper, we study these two questions in the context of the U.S. smartphone industry.

For the first question, in theory, it is possible that oligopolistic competition results in either excessive or insufficient product proliferation. On the one hand, a profit-maximizing firm will have a product in the market as long as the profit gains are greater than the costs, but some of the profit gains may come from business stealing. Because firms do not take into account this negative externality, there may be too many products. On the other hand, unlike a social planner, firms do not internalize consumer surplus. If consumer surplus increases when a product is added to the market, there may also be too few products. These two effects, which work in opposite directions, are highlighted in Mankiw and Whinston (1986) in the context of firm entry and single-product oligopoly. In a multi-product oligopoly, however, there exists an additional factor influencing the equilibrium product offerings: firms' incentives to avoid cannibalization, which may lead to too few products. Overall, because of these three factors, whether competition leads to too few or too many products in the market is an empirical question.

For the second question, the effect of a merger on product offerings is also theoretically ambiguous. When two firms merge, the merged firm internalizes the business stealing effect and thus may reduce its number of products. This is a direct effect. However, there may also exist a countervailing indirect effect: a merger is likely to soften price competition. As a result, the profit gains from adding a product may be larger, leading to an increase in the number of products.

Combining these two research questions, this paper sheds light on how to adjust the leniency of competition policies when product offerings are endogenous. If competition leads to too many products and a merger reduces product offerings, then merger policies should be more lenient. Conversely, if a merger reduces product offerings when there are already too few products in the market, then merger policies should be stricter.

To study our research questions, we focus on the U.S. smartphone market for several reasons. First, the smartphone industry has been one of the fastest growing industries in the world, with billions of dollars at stake. Worldwide smartphone sales grew from 122 million units in 2007 to 1.4 billion units in 2015 (Gartner (2007) and Gartner (2015)), with about 400 billion dollars in global revenue in 2015 (GfK (2016)). Second, product proliferation is a prominent feature of this industry. For example, in the U.S. market during our sample period, Samsung, on average, simultaneously offered 11 smartphones with substantial quality and price variation.

In order to address our research questions and quantify welfare, we develop a structural model of consumer demand and firms' product and price decisions. We describe the demand side using a random coefficient discrete choice model, where product quality is a linear function of a set of key product characteristics, and consumers have heterogeneous tastes for quality. We describe the supply side using a static three-stage structural model. In the first stage, smartphone firms choose products from a set of potential products, with each product associated with a fixed cost in each

period. In the second stage, these firms set their wholesale prices for carriers based on the product portfolio of each firm as well as realized demand and marginal cost shocks. In the third stage, carriers set their retail prices.

Our data come from the Investment Technology Group (ITG) Market Research. This data set provides information on all smartphone products in the U.S. market between January 2009 and March 2013. For every month during this period, we observe both the price and the quantity of each smartphone sold through each of the four national carriers in the U.S. (i.e., AT&T, T-Mobile, Sprint, and Verizon). In addition, we observe key specifications of each product, such as battery talk time and camera resolution.

Using these data, we estimate our model of smartphone demand and marginal cost following an estimation procedure similar to that in Berry, Levinsohn and Pakes (1995). The estimation results are intuitive: on average, consumers prefer smartphones with longer battery talk time, higher camera resolution, a more advanced chipset, a larger screen, and a lighter weight. We use these results to calculate a product quality index, a linear combination of product characteristics weighted by the respective estimated demand coefficients. We then use our quality index to propose a measure of product variety such that adding a product identical to existing products in terms of the observed key characteristics has no impact on our variety measure. Therefore, this measure allows us to distinguish “meaningful” product differentiation from obfuscation. Our results show that product variety within the U.S. smartphone market increases over time during our sample.

On the supply side, we find that marginal cost increases in quality and decreases over time. We also obtain bounds on fixed costs. Specifically, we assume that the observed product portfolio of a firm is profit maximizing in a Nash equilibrium. Consequently, removing or adding a product should not increase the firm’s profit. Based on these conditions, for any product in the market in a month, we obtain an upper bound of its fixed cost in that month; and for any product not in the data in a given month, we obtain a lower bound.

Based on the estimated demand, marginal cost and fixed cost bounds, we conduct counterfactual simulations to address our research questions. To answer the question of whether there are too few or too many products in the market, we conduct two sets of counterfactual simulations for March 2013, the last month in our sample period. In one set of counterfactual simulations, we remove products while in the other set, we add products. To separate product variety from product innovation, we remove (add) only products below the quality frontier of each firm.¹ Our results show that removing a product decreases total surplus, even considering the maximum saving in the fixed cost. These results are robust no matter which product or which two products we remove. In the second set of simulations, we add a product that fills a gap in the quality spectrum. We find that consumer surplus, carrier surplus, and smartphone firms’ total variable profit all increase. The change in total welfare is the sum of these increases minus the fixed cost of the added product.

¹See Yang (2016) for a related study on innovation in the smartphone industry and its upstream chipset industry.

We find that the former is about 2.3 times the lower bound of the latter. Therefore, as long as the fixed cost is not more than 2.3 times of its lower bound, total surplus should increase. To put this ratio in perspective, note that the average upper bound is about 1.2 times of the average lower bound we obtain in our estimation. Overall, these counterfactual simulation results suggest that there are too few products under oligopolistic competition.

Turning to the second research question of how a change in competition affects product offerings, we simulate the effect of a hypothetical merger between Samsung and LG on product offerings, prices, and welfare in March 2013. We also repeat the simulation for a Samsung-Motorola merger and an LG-Motorola merger. Again, to separate product variety from innovation, we allow firms to adjust only those products below their quality frontier. However, different from addressing the first research question, for which we only need to compute the new pricing equilibrium given certain product offerings in the market, we now need to compute the post-merger equilibrium in both product choice and pricing. Computing the product-choice equilibrium is challenging because, in theory, a firm can drop any subset of its current products or add any number of new products after a merger, leading to a large action space. To keep the problem tractable, we restrict the set of potential products for each firm to those offered by this firm in either February or March 2013, plus two additional products that vary in quality. Even with this restriction, a firm’s action space can still be prohibitively large. For example, the merged Samsung-LG entity has 31 potential products, implying a choice set of 2^{31} ($\approx 2.4 \times 10^9$) product portfolios. Therefore, to further deal with this computational challenge, we use a heuristic algorithm to find a firm’s best-response product portfolio given the portfolios of its competitors, and embed this optimization algorithm in a best-response iteration to solve for the post-merger product-choice equilibrium. Results from Monte Carlo simulations show that our algorithm performs well at least for optimal product portfolio problems with a small number of potential products.²

Using this algorithm, we find that after the Samsung-LG merger, the number of products in the market decreases. In particular, the merged firm drops 3 products (out of a per-merger combined total of 26 products) while competing firms altogether add one product. This reduction in the overall number of products also decreases product variety. Due to the decrease in product offerings and the accompanying increase in the prices, we find that consumers are worse off and total welfare also decreases after the merger. These findings hold for the other two mergers (Samsung-Motorola and LG-Motorola) as well.

In summary, we find that there are too few products in the market. We also find that a reduction in competition as a result of a merger further decreases product variety. These findings are robust

²In the Monte Carlo simulations, we study product-choice problems where the number of potential products is small enough for us to enumerate all possible product portfolios and determine the optimal one. We find that the failure rate for the heuristic algorithm (i.e., the percentage of simulations where the heuristic algorithm fails to find the true optimal product portfolio) is always lower than 0.3%, regardless of the starting point for the heuristic algorithm.

to several variations to both the demand side and the supply side of the model. The combination of these findings suggests that merger policies may have to be stricter when we take into account the effect of a merger on product offerings in addition to its effect on prices.

By studying the welfare implications of product proliferation and how competition affects them, this paper contributes to the literature of endogenous product choice.³ Two papers in the literature, Fan (2013) and Berry, Eizenberg and Waldfogel (forthcoming), are most closely related to this paper. Fan (2013) also studies the effect of a merger considering firms' endogenous product choices. However, whereas Fan (2013) keeps the number of products fixed, our model allows firms to adjust both the number and composition of products after a merger.⁴ Interestingly, despite the differences in focus and industries, the two papers make similar policy recommendations: merger policies should be tougher when we take into account firms' post-merger adjustments in their product portfolios, whether such adjustments only concern the characteristics of a fixed set of products or also involve changes in the number of products. In another study, Berry, Eizenberg and Waldfogel (forthcoming) examine the optimal level of product variety in a local radio market.⁵ Our study differs from their work by considering product variety in a multi-product oligopoly setting instead of a single-product oligopoly setting. This difference in market structure may explain why they find too much product variety in the local radio market, but we find too few products in the U.S. smartphone industry. As mentioned, compared to a single-product firm, a multiple-product firm has an additional reason for not adding a product: to avoid cannibalization. As a result, in a market with multiple-product firms, it is more likely that there are too few products.

This paper is also related to the stream of research that studies the smartphone industry. For example, Sinkinson (2014) studies the motivations behind the exclusive contract between Apple and AT&T for the early iPhones. In another study, Zhu, Liu and Chintagunta (2015) quantify the welfare effects of this exclusive contract. Luo (2015) examines the operation system network effect. Finally, Yang (2016) studies the effect of vertical integration on innovation in the smartphone industry and its upstream chipset industry. We complement these papers by studying the welfare implications of product choices and the effects of competition with endogenous product choice.

The rest of the paper is organized as follows. We describe the data in Section 2. We develop the model of the smartphone market in Section 3 and present the estimation results in Section 4. Section 5 first describes counterfactual simulations and then discusses the results. We discuss the robustness of the results in Section 6. Finally, we conclude in Section 7.

³Examples in this literature include Seim (2006), Draganska, Mazzeo and Seim (2009), Watson (2009), Chu (2010), Crawford and Yurukoglu (2012), Sweeting (2013), Eizenberg (2014), Nosko (2014), Crawford, Shcherbakov and Shum (2015), Orhun, Venkataraman and Chintagunta (2015) and Wollmann (2016). See Crawford (2012) for a survey of this literature. Examples in the theoretical literature on this topic include Johnson and Myatt (2003) and Shen, Yang and Ye (2016).

⁴Wollmann (2016) studies the importance of accounting for product entry in predicting price changes due to different policies and thus also allows firms to adjust the number of products.

⁵Thomas (2011) studies a similar question from the firm perspective and finds that decentralized decision making by multinational firms leads to too many products in the sense that a firm's profit would increase with fewer products.

2 Data

Our data come from the Investment Technology Group (ITG) Market Research. This data set covers all smartphones sold in the U.S. market between January 2009 and March 2013. For every carrier in the U.S. and every month during our sample period, we observe the price and sales for each smartphone sold through that carrier in that month. We also observe key specifications of each product such as battery talk time and camera resolution.

The price information provided by the ITG for the four major national carriers (AT&T, Verizon, Sprint, and T-Mobile) is the so-called subsidized price or the average price for a smartphone device that a carrier charges a consumer who uses this carrier’s network service.⁶ Note that the subsidized price for a smartphone is not the true cost of buying the smartphone because the consumer also needs to pay for the service plan. As will be explained later, we include carrier/year-specific fixed effects in the model to capture the average service cost for a consumer. Furthermore, since non-major or fringe carriers often provide only prepaid service plans and serve only one regional market, we drop these observations from our analyses.⁷

In the end, our sample consists of 3256 observations, each of which is a smartphone/carrier/month combination. Table 1 presents the summary statistics on the quantity, price and product characteristics. The average monthly sales of a product are around 77,000 while the standard deviation of the monthly sales is about twice the mean. There is also a sizable variation in price across observations: the price is 122 dollars on average, with a standard deviation of 85. For each product, we observe product characteristics such as battery talk time, camera resolution, screen size measured by the diagonal of the screen, and weight. We also observe the generation of the chipset used by each product. For example, there are five Apple smartphones in our data (i.e., iPhone 3G, iPhone 3Gs, iPhone 4, iPhone 4s and iPhone 5), each of which uses a chipset of a different generation. The standard deviations of these product characteristics are about 17% to 47% of their corresponding means, indicating a wide variety of products across our sample.

There are 18 smartphone firms and 260 smartphones in the sample. Table 2 lists the top six firms according to their average monthly smartphone sales: Apple, Samsung, BlackBerry, HTC, Motorola and LG. From Table 2, we see that Apple is the undisputed leader in the industry, with an average monthly sales of about 2 million units, followed by Samsung with an average monthly sales of 0.76 million. The table also shows that all of these six firms offer multiple products simultaneously. For example, on average, Samsung offers 11 products in a given month, followed by HTC with an average of 10 products in a given month.

Table 3 shows that the multiple products offered by a firm have different qualities and prices.

⁶The average is taken over transactions in a month. Note that the carrier fee structure is relatively stable during our sample period. In April 2013 (right after our sample period), however, T-Mobile launched an “Uncarrier” campaign, which abandoned service contracts and subsidies for devices. Other carriers followed suit.

⁷The total U.S. market share of these fringe carriers in terms of smartphones sold is about 10%.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max
Quantity (1000)	77.54	146.04	0.04	1419
Price (\$)	122.16	85.24	0 ^a	406.9
Battery talk time (hours)	7.08	2.93	3	22
Camera resolution (megapixel)	4.65	2.18	0 ^b	13
Chipset generation 2 dummy	0.23	0.42	0	1
Chipset generation 3 dummy	0.25	0.43	0	1
Chipset generation 4 dummy	0.14	0.34	0	1
Chipset generation 5 dummy	0.09	0.29	0	1
Screen size (inch)	3.44	0.73	2.20	5.54
Weight (gram)	135.31	22.72	89.5	193
Observations (smartphone/carrier/months)	3256			

^aFour observations in our sample have a 0 price.

^bOne product in our sample (BlackBerry 8830) does not have a camera.

Table 2: List of Top Six Smartphone Firms

Firm	Headquarters	Avg. Monthly Sales ^a (million units)	Avg. Number of Products ^a
Apple	U.S.	1.99	2.10
Samsung	Korea	0.76	11.08
BlackBerry	Canada	0.61	8.33
HTC	Taiwan	0.60	10.35
Motorola	U.S.	0.46	7.90
LG	Korea	0.33	6.76

^aAveraged across months.

In this table, we report two within-(firm/month) dispersion measures for price and product characteristics. To calculate within-(firm/month) price dispersion, for example, we first compute the standard deviation of price across all observations of a given firm in a given month. We set the standard deviation to 0 for firm/months with a single observation. We then take the average of these standard deviations across all 557 firm/months in the sample, and report this average in Column 1 of Table 3. Similarly, we compute the difference between the highest and the lowest price among all observations in the same firm/month and take the average across firm/months to obtain the average range within a firm/month, as shown in Column 2. We find that the average within-(firm/month) standard deviation in price is 42.42 dollars, which is about 1/2 of the overall standard deviation of price across all observations (see Table 1), implying that within-(firm/month) variation is an important component of total price variation. The within-(firm/month) variation of product characteristics is also significant. For example, Column 2 for chipset generation shows that smartphone firms on average simultaneously offer products whose chipsets are one generation apart. Overall, Table 3 provides evidence for product proliferation in smartphone industry.

Table 3: Summary Statistics on Quality and Price Dispersion within a Firm/month

	Average	Std. Dev.	Average Range
Price (\$)	42.42		122.50
Battery talk time (hours)	1.04		3.10
Camera resolution (megapixel)	0.81		2.16
Chipset generation	0.36		0.93
Screen size (inch)	0.21		0.61
Weight (gram)	11.12		32.23

3 Model

3.1 Demand

In this section, we develop our model. We begin with the demand side, which we describe using a random-coefficient discrete choice model. Since our data are aggregated at the smartphone/carrier/month level, we assume that a consumer’s choice is a smartphone/carrier combination, indexed by j . Furthermore, we assume that the utility that consumer i gets from purchasing j in period t is:

$$u_{ijt} = \beta_i q_j - \alpha p_{jt} + \lambda_{m(j)} + \kappa_{c(j)t} + \xi_{jt} + \varepsilon_{ijt}, \quad (1)$$

where q_j is a quality index which depends on the observable product characteristics \mathbf{x}_j as $q_j = \mathbf{x}_j \boldsymbol{\theta}$, where $\boldsymbol{\theta}$ are parameters to be estimated. The random coefficient β_i captures consumers’ heterogeneous tastes for quality and is assumed to follow a normal distribution with mean β and variance σ^2 . Since we cannot separately identify β , σ and $\boldsymbol{\theta}$ as they enter the utility function as $\beta \boldsymbol{\theta}$ and $\sigma \boldsymbol{\theta}$, we normalize the first dimension of $\boldsymbol{\theta}$ to be 1. Finally, we denote the price of j in period t by p_{jt} .

To capture consumers’ average taste for a brand, we include a brand fixed effect, $\lambda_{m(j)}$, where $m(j)$ represents the smartphone firm (i.e., the brand) of j . To capture the average quality and cost of carrier c ’s network service in period t as well as a general time trend in consumers’ tastes for smartphones, we include a carrier/year fixed effect.⁸ Finally, to capture seasonality in demand, we include a quarter fixed effect. For simplicity of notation, we denote both the carrier/year fixed effect and the quarter fixed effect by one term $\kappa_{c(j)t}$, where $c(j)$ represents the carrier of choice j . The term ξ_{jt} represents a demand shock, and the error term ε_{ijt} captures consumer i ’s idiosyncratic taste, which is assumed to be i.i.d. and to follow a type-I extreme value distribution. We normalize the mean utility of the outside option to be 0. Thus, the utility of the outside option is $u_{i0t} = \varepsilon_{i0t}$.

Under the type-I extreme value distributional assumption of ε_{ijt} , we can express the market

⁸By using fixed effects to capture service plan features and prices, we implicitly assume that they are exogenous. We do so for two reasons. First, we do not have data on carriers’ service plans. It is also difficult to compare service plans provided by different carriers as they differ in many dimensions. Second, a carrier typically does not redesign its service plans when a new smartphone is introduced to the market. Thus, it is plausible to assume that carriers’ service plans are exogenous to smartphone firms’ product and price decisions.

share of choice j in period t as:

$$s_{jt}(\mathbf{q}_t, \mathbf{p}_t, \boldsymbol{\xi}_t) = \int \frac{\exp(\beta_i q_j - \alpha p_{jt} + \lambda_{m(j)} + \kappa_{c(j)t} + \xi_{jt})}{1 + \sum_{j' \in \mathcal{J}_t} \exp(\beta_i q_{j'} - \alpha p_{j't} + \lambda_{m(j')} + \kappa_{c(j')t} + \xi_{j't})} dF(\beta_i), \quad (2)$$

where \mathcal{J}_t denotes the set of all products in period t , $\mathbf{q}_t = (q_j, j \in \mathcal{J}_t)$ is a vector of the quality indices of all products in the market, and \mathbf{p}_t and $\boldsymbol{\xi}_t$ are analogously defined. Finally, $F(\beta_i)$ represents the distribution function of the random coefficient β_i .

Following Berry, Levinsohn and Pakes (1995), we define the mean utility of j in period t as

$$\delta_{jt} = \beta q_j - \alpha p_{jt} + \lambda_{m(j)} + \kappa_{c(j)t} + \xi_{jt}, \quad (3)$$

and invert it out based on equation (2).

3.2 Supply

We use a static three-stage game to describe the supply side of the model. In the first stage, firms choose their products. In the second stage, firms choose the wholesale prices charged to the carriers based on realized demand and marginal cost shocks. In the third stage, carriers choose the subsidized retail prices. We describe these three stages in reverse order.

3.2.1 Decisions on Prices

In the final stage of our model, carriers observe the set of products available on each carrier (denoted by \mathcal{J}_{ct}), wholesale prices (w_{jt}) and demand shocks (ξ_{jt}). They choose the retail prices (p_{jt}) to maximize their respective profit. Suppose that the profit that carrier c obtains through its service is b_{ct} per consumer. Thus, carrier c 's profit for each unit of a product sold is $p_{jt} + b_{ct} - w_{jt}$. We do not observe b_{ct} or w_{jt} . However, we can invert out $\tilde{w}_{jt} = w_{jt} - b_{c(j)t}$ from the first-order condition on p_{jt} . Specifically, carrier c 's profit-maximizing problem is

$$\max_{p_{jt}, j \in \mathcal{J}_{ct}} \sum_{j \in \mathcal{J}_{ct}} N s_{jt}(\mathbf{q}_t, \mathbf{p}_t, \boldsymbol{\xi}_t) (p_{jt} - \tilde{w}_{jt}), \quad (4)$$

where N is the market size. The first-order condition allows us to invert out \tilde{w}_{jt} as:

$$\tilde{w}_{jt} = p_{jt} + [\Delta_{ct}^{-1} \mathbf{s}_{ct}]_{jt}, \quad (5)$$

where Δ_{ct} represents a $|\mathcal{J}_{ct}| \times |\mathcal{J}_{ct}|$ matrix whose (j, j') element is $\frac{\partial s_{j't}}{\partial p_{jt}}$, and $\mathbf{s}_{ct} = (s_{jt}, j \in \mathcal{J}_{ct})$. We denote the equilibrium of this stage by $p_{jt}^*(\tilde{\mathbf{w}}_t, \mathbf{q}_t, \boldsymbol{\xi}_t)$, where $\tilde{\mathbf{w}}_t = (\tilde{w}_{jt}, j \in \mathcal{J}_t)$ and $(\mathbf{q}_t, \boldsymbol{\xi}_t)$ are analogously defined in Section 3.1.

In the second stage, smartphone firms choose wholesale prices that they charge carriers after

observing demand and marginal cost shocks. We assume that marginal cost depends on product quality (q_j), time fixed effects (γ_t), and a jt -specific shock (η_{jt}).⁹ Specifically, we assume that the marginal cost is $mc_{jt} = \gamma_t + \gamma_1 \exp(q_j) + \eta_{jt}$. If we let $\tilde{m}c_{jt} = mc_{jt} - b_{c(j)t}$ and $\tilde{\gamma}_{ct} = \gamma_t - b_{ct}$, we can re-write the marginal cost as:

$$\tilde{m}c_{jt} = \tilde{\gamma}_{c(j)t} + \gamma_1 \exp(q_j) + \eta_{jt}. \quad (6)$$

A smartphone firm m 's profit-maximizing problem is therefore

$$\max_{\tilde{w}_{jt}, j \in \mathcal{J}_{mt}} \sum_{j \in \mathcal{J}_{mt}} (\tilde{w}_{jt} - \tilde{m}c_{jt}) N s_{jt}(\mathbf{q}_t, \mathbf{p}_t^*(\tilde{\mathbf{w}}_t, \mathbf{q}_t, \boldsymbol{\xi}_t), \boldsymbol{\xi}_t), \quad (7)$$

where \mathcal{J}_{mt} represents the choices offered by firm m in period t . The first-order condition is

$$s_{jt} + \sum_{j' \in \mathcal{J}_{mt}} (\tilde{w}_{j't} - \tilde{m}c_{j't}) \left(\sum_{j'' \in \mathcal{J}_t} \frac{\partial s_{j't}}{\partial p_{j''t}} \frac{\partial p_{j''t}^*}{\partial \tilde{w}_{jt}} \right) = 0, \quad (8)$$

or equivalently,

$$\tilde{w}_{jt} + [\Delta_{mt}^{-1} \mathbf{s}_{mt}]_{jt} = \tilde{\gamma}_{c(j)t} + \gamma_1 \exp(q_j) + \eta_{jt}, \quad (9)$$

where $\mathbf{s}_{mt} = (s_{jt}, j \in \mathcal{J}_{mt})$, and Δ_{mt} represents a $|\mathcal{J}_{mt}| \times |\mathcal{J}_{mt}|$ matrix whose (j, j') element is $\left(\sum_{j'' \in \mathcal{J}_t} \frac{\partial s_{j't}}{\partial p_{j''t}} \frac{\partial p_{j''t}^*}{\partial \tilde{w}_{jt}} \right)$. Combining equations (5) and (9) yields

$$p_{jt} + [\Delta_{ct}^{-1} \mathbf{s}_{ct}]_{jt} + [\Delta_{mt}^{-1} \mathbf{s}_{mt}]_{jt} = \tilde{\gamma}_{c(j)t} + \gamma_1 \exp(q_j) + \eta_{jt}, \quad (10)$$

which we bring to the data for estimation.

As can be seen from equation (10), this pricing model is a simple linear pricing model, which implies double marginalization. In Section 6, we consider several alternative pricing models for robustness analyses.

3.2.2 Decisions on Products

In the first-stage of the model, firms choose products. Smartphone firms typically offer a few flagship products and a set of non-flagship products. For example, Samsung offers Galaxy S series products as its flagship products as well as a set of non-flagship products. In total, there are 39 flagship smartphones in our data.¹⁰ Flagship products are usually equipped with cutting-edge

⁹Note that j indexes a smartphone/carrier combination. Therefore, the marginal cost shock occurs at the smartphone/carrier/time level. Marginal cost may vary across carriers because different radio technologies are used for products sold by different carriers. Moreover, carriers sometimes require firms to preload specific software on a smartphone, contributing to cost differences.

¹⁰See Appendix A for a list of the 39 flagship smartphones in our data.

technologies and thus require a sizable sunk innovation cost. To separate product variety from product innovation, in our analyses, we take the set of flagship products in the market as a given, and focus instead on how firms choose their non-flagship products.¹¹

There is a fixed cost for every product. Since non-flagship products are behind the technology frontier, we assume that there is no sunk cost of introducing a new non-flagship product. There is only a (flow) fixed cost that occurs every period. Therefore, similar to Eizenberg (2014), we treat product choice as static. Nash equilibrium implies that given competitors' product portfolios at the equilibrium, any deviation from a firm's equilibrium product portfolio should not lead to a higher expected profit for this firm, where the expectation is taken over demand and marginal cost shocks. Specifically, we consider two types of deviations: removing a product in the data or adding a product not in the data. For both types of deviations, we restrict the product to be a non-flagship product. Note that while the majority of the non-flagship products in our study are sold through only one carrier, 14 out of the 221 non-flagship products are sold through either two or three carriers. Therefore, to distinguish a smartphone/carrier combination (indexed by j) from a smartphone product, we index the latter by \tilde{j} . Similarly, $\tilde{\mathcal{J}}_{mt}$ represents all smartphones of m , i.e., m 's product portfolio; and $\tilde{\mathcal{J}}_t$ represents all smartphones in the market in period t .

We first consider the case when a product is removed. Here, firm m 's expected profit should not increase if product \tilde{j} in its portfolio is removed, i.e.,

$$E_{(\boldsymbol{\xi}_t, \boldsymbol{\eta}_t)} \pi_{mt}(\mathbf{q}_t, \boldsymbol{\xi}_t, \boldsymbol{\eta}_t) - F_{\tilde{j}t} \geq E_{(\boldsymbol{\xi}_t, \boldsymbol{\eta}_t)} \pi_{mt}(\mathbf{q}_t \setminus q_{\tilde{j}}, \boldsymbol{\xi}_t \setminus \xi_{\tilde{j}t}, \boldsymbol{\eta}_t \setminus \eta_{\tilde{j}t}) \text{ for any } \tilde{j} \in \tilde{\mathcal{J}}_{mt}, \quad (11)$$

where $\pi_{mt}(\mathbf{q}_t, \boldsymbol{\xi}_t, \boldsymbol{\eta}_t)$ is the equilibrium variable profit for firm m (at the stage-2 and stage-3 pricing equilibrium), $\pi_{mt}(\mathbf{q}_t \setminus q_{\tilde{j}}, \boldsymbol{\xi}_t \setminus \xi_{\tilde{j}t}, \boldsymbol{\eta}_t \setminus \eta_{\tilde{j}t})$ is firm m 's variable profit if product \tilde{j} is removed from its product portfolio, and $F_{\tilde{j}t}$ is the fixed cost.¹² Inequality (11) gives an upper bound of $F_{\tilde{j}t}$ for $\tilde{j}t$ in the data. Intuitively, for products in the market, their fixed costs should be bounded from above.

We next consider the case when a product is added. Here, firm m 's expected profit should not increase if a potential product \tilde{j} such that $\tilde{j} \notin \tilde{\mathcal{J}}_{mt}$ is added to its product portfolio. The corresponding inequality is

$$E_{(\boldsymbol{\xi}_t, \boldsymbol{\eta}_t)} \pi_{mt}(\mathbf{q}_t, \boldsymbol{\xi}_t, \boldsymbol{\eta}_t) \geq E_{(\boldsymbol{\xi}_t, \boldsymbol{\eta}_t)} \pi_{mt}(\mathbf{q}_t \cup q_{\tilde{j}}, \boldsymbol{\xi}_t \cup \xi_{\tilde{j}t}, \boldsymbol{\eta}_t \cup \eta_{\tilde{j}t}) - F_{\tilde{j}t} \text{ for any } \tilde{j} \notin \tilde{\mathcal{J}}_{mt}. \quad (12)$$

¹¹Moreover, flagship products are sold globally. Studying firms' decisions on them, therefore, requires us to make the assumption that the demand function estimated using the U.S. data captures the global demand well. In other words, we need to rule out substantial cross-country variation in either the set of products offered in a country or the consumer taste. In contrast, non-flagship products are behind the technological frontier and are often sold in the U.S. market only. As a result, having data on the U.S. market is sufficient for studying firms' product-choice decisions about them.

¹²When product \tilde{j} is one of the 14 non-flagship products sold through multiple carriers, the fixed cost reflects the cost of having the product on the observed multiple carriers. Therefore, later in counterfactual simulations, if a firm drops a product, it drops the product from all carriers. We have conducted robustness analyses where we re-estimate the fixed cost bounds for each smartphone/carrier combination and allow firms to drop each smartphone/carrier separately. Our findings are robust.

This inequality yields a lower bound of $F_{\tilde{j}t}$ for any $\tilde{j}t$ such that $\tilde{j} \notin \tilde{\mathcal{J}}_t$. This is again intuitive because the fixed cost of a not-offered product should be bounded from below. Note that such a potential product \tilde{j} can be any product not in the data. In Sections 4 and 5, we explain the potential products we consider in the estimation and the counterfactual simulations.

4 Estimation

4.1 Estimation Procedure

The estimation of demand and marginal costs is similar to that in Berry, Levinsohn and Pakes (1995). We construct moments using equations (3) and (10), and estimate the parameters using the Generalized Method of Moments. Following the literature, our instrumental variables are based on the characteristics of other products of the same firm or the products of the competing firms. Similar to Berry, Levinsohn and Pakes (1995), this estimation strategy relies on the timing assumption that the shocks are realized after the product choice. Note that we control for systematic brand effects, carrier effects, and time effects using various fixed effects. Therefore, it seems reasonable (though imperfect) to assume that any product/month-specific shocks are uncorrelated with product characteristics. In addition to the above instruments, we include the four-month lagged exchange rates of the Chinese, Japanese and Korean currencies to U.S. dollars as a cost shifter in the instruments.

As for the fixed cost, we use inequalities (11) and (12) to obtain the bounds for the non-flagship products. Using inequality (11), we calculate the upper bound of $F_{\tilde{j}t}$ as (the opposite of) the change in the expected variable profit when product \tilde{j} is removed, i.e., $E_{(\boldsymbol{\xi}_t, \boldsymbol{\eta}_t)} \pi_{mt}(\mathbf{q}_t, \boldsymbol{\xi}_t, \boldsymbol{\eta}_t) - E_{(\boldsymbol{\xi}_t, \boldsymbol{\eta}_t)} \pi_{mt}(\mathbf{q}_t \setminus q_{\tilde{j}}, \boldsymbol{\xi}_t \setminus \xi_{\tilde{j}t}, \boldsymbol{\eta}_t \setminus \eta_{\tilde{j}t})$. The expectation is taken over the demand and marginal cost shocks $(\boldsymbol{\xi}_t, \boldsymbol{\eta}_t)$. We assume that they each follows a normal distribution and obtain the estimates of their means and standard deviations based on the estimated $(\hat{\boldsymbol{\xi}}_t, \hat{\boldsymbol{\eta}}_t)$. To compute the expected variable profit, we draw these shocks from their respective estimated distributions. We first compute the pricing equilibrium and calculate the resulting variable profit for each draw, and then take the average of these variable profits across all draws. Using inequality (12), we calculate the lower bound similarly for any $\tilde{j}t$ such that $\tilde{j} \notin \tilde{\mathcal{J}}_t$.

4.2 Estimation Results

Table 4 reports the estimation results on demand and marginal cost. Our demand estimation results indicate that consumers on average favor products with longer battery talk time, higher camera resolution, a more advanced chipset, a larger screen and a lighter weight. For example, we find that a one-hour increase in battery talk time is equivalent to a price decrease of 6.5 dollars for an average consumer. Similarly, a one-megapixel increase in camera resolution is equivalent to a

Table 4: Estimation Results

	Parameter	Std. Error
Demand		
Quality coefficient		
battery talk time (hours)	0.056***	0.013
camera resolution (megapixel)	0.093***	0.036
chipset generateion 2	0.460***	0.113
chipset generateion 3	0.718***	0.147
chipset generateion 4	1.055***	0.200
chipset generateion 5	1.674***	0.280
screen size (inch)	1	
weight (gram)	-0.002*	0.001
Quality random coefficient		
mean	0.779***	0.128
std. dev.	0.300***	0.079
Price	-0.007***	0.002
Apple	2.779***	0.094
BlackBerry	1.237***	0.121
Samsung	0.338***	0.069
Flagship?	0.597***	0.065
Carrier/year and quarter dummies		Yes
Marginal Cost (\$)		
Exp(quality/10)	518.521***	2.504
Apple	-30.221***	0.115
BlackBerry	98.749***	0.433
Samsung	-20.413***	0.131
Carrier/year dummies		Yes

* indicates 90% level of significance. *** indicates 99% level of significance.

price decrease of 10.9 dollars, while an increase in the screen size by 0.1 inches is equivalent to a price decrease of 11.7 dollars. Finally, we find that each generation upgrade is equivalent to a price drop between 30 to 78 dollars. The estimated standard deviation of consumers' taste for quality is about 40% of the average taste, suggesting that consumers are heterogenous in their willingness-to-pay for quality. In our estimation, we include Apple, BlackBerry and Samsung dummies and group all other brands as a baseline brand in the utility function. Our estimates show that there is a large premium for Apple (417 dollars), followed by BlackBerry, and then Samsung.¹³ Our estimation results also suggest that there is an advantage to be a flagship product, which is probably related to firms' differential advertising spending on flagship versus non-flagship products.

Table 5 reports the price semi-elasticities for top-five products on AT&T in March 2013: Motorola's Atrix HD, Samsung's Galaxy S III and Apple's iPhone 4, iPhone 4s and iPhone 5. The

¹³Note that even though the estimated BlackBerry-dummy coefficient is larger than that of Samsung, considering the product characteristics, the average quality of Samsung products in a month is generally higher than that of BlackBerry products, especially later in our sample.

table shows that a \$10 increase in the price of a product leads to about 6% decrease in its demand.¹⁴ Unsurprisingly, the own price semi-elasticities are larger than the cross semi-elasticities.

We construct the quality index for each product based on the estimated coefficients of the product characteristics. Table 6 reports the elasticities of quality based on the estimated quality index, again for the top-five AT&T products in March 2013. Across all five products, we see that a 1% increase in the quality index corresponds to about a 5% to 8% increase in sales.

Table 5: Demand Semi-Elasticities with Respect to Price

	Atrix HD	Galaxy S III	iPhone 4	iPhone 4s	iPhone 5
Atrix HD	-6.600	0.089	0.160	0.213	0.398
Galaxy S III	0.065	-6.570	0.163	0.217	0.409
iPhone 4	0.047	0.066	-6.526	0.175	0.309
iPhone 4s	0.052	0.073	0.145	-6.476	0.337
iPhone 5	0.058	0.083	0.155	0.203	-6.289

Note: Top-five products on AT&T in in March 2013. (Row i , Column j): percentage change in market share of product j with a \$10 change in product i 's retail price.

Table 6: Demand Elasticities with Respect to Quality

	Atrix HD	Galaxy S III	iPhone 4	iPhone 4s	iPhone 5
Atrix HD	7.875	-0.125	-0.148	-0.224	-0.488
Galaxy S III	-0.087	8.207	-0.152	-0.23	-0.506
iPhone 4	-0.059	-0.086	5.168	-0.173	-0.357
iPhone 4s	-0.066	-0.098	-0.129	5.906	-0.397
iPhone 5	-0.077	-0.114	-0.141	-0.21	6.762

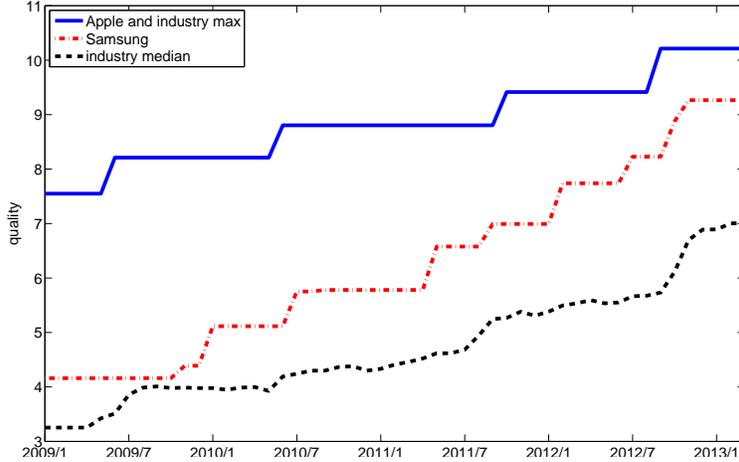
Note: Top-five products on AT&T in in March 2013. (Row i , Column j): percentage change in market share of product j with a 1 percentage change in product i 's quality.

To see the evolution of smartphone quality over time, we divide the brand fixed effects by the mean taste for quality and then add it to the quality index. In Figure 1, we plot the maximum and median of this index across all products in each month. We also plot the maximum of this index for Apple and Samsung, respectively. Figure 1 shows that the Apple quality frontier line perfectly coincides with the industry quality frontier line and that this line experiences a discrete jump whenever a new iPhone product is introduced, confirming the perception that iPhone products drive the quality frontier. Figure 1 also shows that the median quality index stays at a relatively constant distance from the frontier and that Samsung has narrowed the quality gap between its smartphone products and Apple's iPhones.

We use the same quality index used in Figure 1 to construct a measure of product variety and show its evolution over time. Specifically, we measure product variety in a market with n products

¹⁴Given that we have data on only the subsidized retail price, which is not the actual price for a consumer to buy a smartphone, we do not compute the price elasticity.

Figure 1: Smartphone Quality over Time



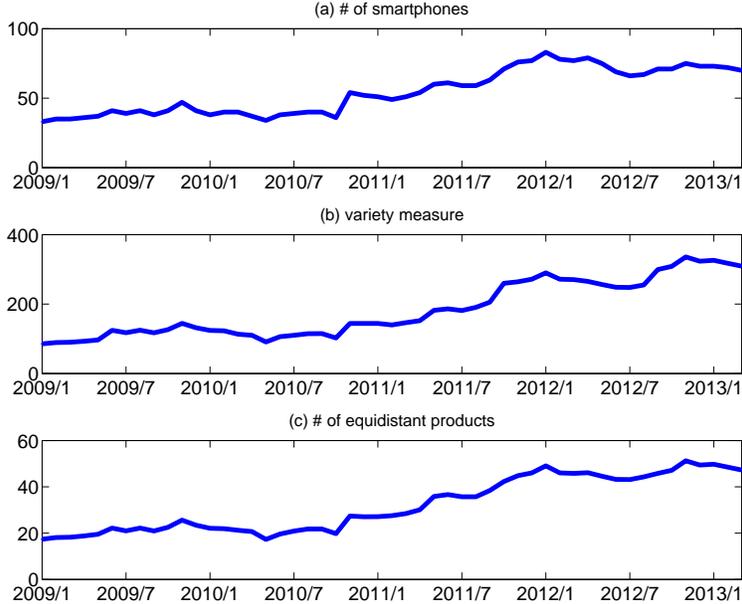
as $\left[\sum_{k=2}^n (q^{(k)} - q^{(k-1)})^{1/2} \right]^2$, where $q^{(1)} < \dots < q^{(n)}$ are the qualities of the n products sorted in an ascending order. Note that this measure resembles the CES utility function, and has three desirable properties. First, given the quality range (i.e., $q^{(n)} - q^{(1)}$), this measure is maximized when products are equidistant. The maximum is $(n - 1) (q^{(n)} - q^{(1)})$. Second, this maximum is increasing in the number of products n and the quality range $(q^{(n)} - q^{(1)})$. Third, adding a product identical to one of the existing products in terms of the key observable characteristics (and hence also in terms of the quality index) has no impact on the product variety measure. In other words, if firms take a strategy of obfuscation, i.e., add products that differ from existing products only in trivial features such as names or colors, our product variety measure will recognize such a strategy and will not count such products in measuring variety.

Given the first property of the product variety measure, we can give the following “as if” interpretation to the measure: a value of x for the product variety measure is as if there are $x/(q^{(n)} - q^{(1)}) + 1$ equidistant products. In Figure 2, we plot the number of smartphones, our measure of product variety, and the “as if” number of equidistant products every month during our sample. Figure 2(a) shows that the number of smartphones available in the market increases over time, from 33 in January 2009 to 70 in March 2013. This increase is accompanied by an increase in both the product variety measure (see Figure 2(b)) and the “as if” number of equidistant products (see Figure 2(c)), indicating that the increase in the number of smartphones is not completely driven by obfuscation.

On the supply side, we find that marginal cost increases in product quality. Though not reported in Table 4, the estimated carrier/year fixed effects indicate that marginal cost is decreasing over time.¹⁵ Based on the estimates of the demand and marginal cost functions, we obtain an upper

¹⁵It should be noted that the estimated marginal cost is, in fact, a smartphone firm’s marginal cost minus the

Figure 2: Product Variety over Time



bound of the fixed cost for each non-flagship smartphone/month combination in the data. The average upper bound, averaged across all such smartphone/month combinations, is 6.16 million dollars.¹⁶ Figure 3(a) plots these upper bounds. The horizontal axis represents the quality of a product, the same quality index in Figure 1. The vertical axis represents the upper bound of the fixed cost. Figure 3(a) suggests that the upper bound of the fixed cost is positively correlated with product quality. In Figure 3(b), we plot the lower bounds for discontinued non-flagship products.¹⁷ The average lower bound is 5.27 million dollars.

5 Counterfactual Simulations

In this section, we conduct counterfactual simulations to address the two research questions of interest. In all counterfactual simulations, we keep the set of flagship products as fixed and only allow the number and the composition of non-flagship products to be adjusted.¹⁸ Therefore, for simplicity of exposition, a product in this section refers to a non-flagship product whenever it is

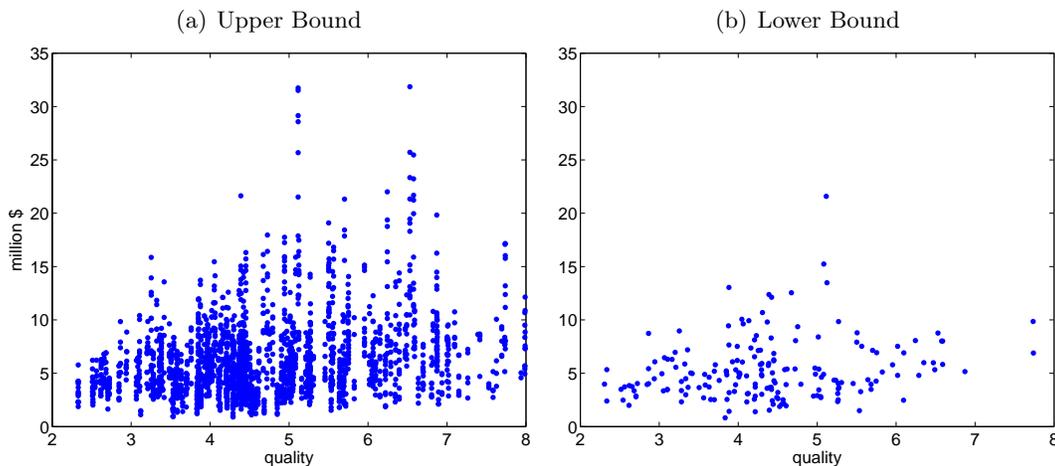
carrier's per-consumer service profit. The estimated time trend, therefore, accounts for changes in the marginal cost of smartphones as well as changes in the service profit of a carrier.

¹⁶As mentioned, 14 non-flagship smartphones are sold through several carriers. In reporting this statistic, we divide the upper bound for each smartphone/month by the corresponding number of carriers. When we do not do so, this average upper bound becomes 6.58.

¹⁷There are 7 smartphone/month combinations where a product is discontinued from multiple carriers. For these smartphone/months, we report the lower bound of the fixed cost of having this smartphone provided through each carrier separately.

¹⁸In a robustness analysis where we allow firms to also adjust old flagship products, we obtain the same results, i.e., we find that firms do not adjust these products.

Figure 3: Bounds of Fixed Costs (Million \$)



not explicitly specified.

5.1 Are there too few or too many products?

There are two reasons why product offerings in an oligopoly market are inefficient. First, given the competitors' products, a firm chooses to offer a product as long as the marginal profit from doing so is positive. However, the firm does not consider the potential negative externality from stealing market share when making its decisions. As a result, there might be too many products in the market from a welfare point of view. Second, consumer surplus is not part of a firm's objective function. If consumer surplus increases when a product is added to the market, there might also be too few products. Because of these two potentially countervailing forces, whether there are too few or too many products is an empirical question.

To address this question, we first conduct counterfactual simulations where we remove a product.¹⁹ Specifically, for March 2013, the last month of our data, we remove the lowest-quality product in the month, solve for the new pricing equilibrium, and then compute the corresponding consumer surplus and producer surplus. We repeat this counterfactual simulation removing the median (highest)-quality product, and report the results in Table 7. Each column of the table corresponds to a simulation where a different product is removed. In the first three rows of the table, we report changes in consumer surplus, carrier surplus (i.e., the sum of carriers' profits) and the sum of smartphone firms' variable profits. All three measures are expectations over the demand and the marginal cost shocks. In the last row, we report the upper bound of the removed product's fixed cost, which is the maximum possible saving in fixed costs.

The results across all three columns of Table 7 show that consumers are worse off when a product

¹⁹For any product removed, we remove it from all carriers.

Table 7: Welfare Changes when a Product is Removed, March 2013 (million \$)

Removed product	Lowest-quality	Median	Highest
$\Delta(\text{consumer surplus})$	-0.92	-2.52	-12.67
$\Delta(\text{carrier surplus})$	-0.83	-1.39	-9.13
$\Delta(\text{smartphone producer variable profits})$	-0.50	-0.90	-3.24
Upper bound of savings in fixed costs	0.94	2.19	12.14

is removed. This is partially due to changes in prices after the product is removed, but mainly because of the direct effect of removing the product. Specifically, when we hold the prices of the remaining products fixed, we find that changes in consumer surplus are (-0.94, -2.19, -11.57) million dollars across the three columns, which account for most of the total change in consumer surplus. To put these changes in consumer surplus in perspective, note that the average monthly sales of a product is 77540 units and the average subsidized price is 122 dollars (see Table 1). Considering an average service plan price of 60 dollars per month over 24 months, consumers pay a total of $(60 \times 24 + 122) \times 77540$ dollars, which is about 10 times the consumer surplus from removing the highest-quality product.

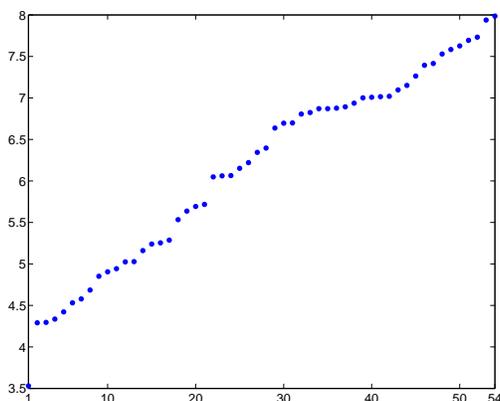
Carriers' profits also drop. As for smartphone firms, the comparison of the third row and the last row shows that if the fixed cost is at its upper bound, the total smartphone producer surplus increases after a product is removed. This result confirms the intuition that because firms do not internalize the business stealing effect, there may be excessive product proliferation, especially if the fixed cost is high. However, this effect is dominated by the effect of product offerings on consumer surplus: summing over the four rows of Table 7, we see that removing a product leads to a decrease in total welfare, even considering the maximum possible saving in the fixed cost. One concern with this finding is that the decrease in consumer surplus may be overestimated because when we drop a product, we drop the Logit error term corresponding to this product, which is independent of other Logit error terms and has a support from $-\infty$ to ∞ . To address this concern, we recalculate $\Delta(\text{consumer surplus})$ ignoring this change in the Logit error. The changes in consumer surplus are indeed smaller: they become -0.06, -0.45, and -7.87 million dollars. However, the sum of the four rows is still negative.

Comparing results across the three columns, we can see that the changes in all welfare measures become larger as we move from removing the lowest to the highest-quality product. The main conclusion, however, remains the same: total welfare decreases even considering the maximum possible saving in the fixed cost. In fact, when we repeat the above exercise for each of the 54 products in March 2013, we find that our results hold in all 54 simulations. Specifically, $\Delta(\text{consumer surplus})$, $\Delta(\text{carrier surplus})$ and $\Delta(\text{smartphone producer variable profits})$ are always negative; the sum of them plus the upper bound of the removed product's fixed cost is always negative. These results indicate that removing any product in the market leads to a decrease in total welfare, even consid-

ering the maximum possible saving in the fixed cost. Finally, because it is a theoretical possibility that removing multiple products together may increase total welfare, we have also repeated the exercise removing any two products and find that the conclusion still holds.

In summary, the above results suggest that removing any one or two of the existing products in this market is welfare-decreasing. However, does adding a product lead to an increase in welfare? To answer this question, we consider adding a product that fills a gap in the quality spectrum. Specifically, we plot the qualities of the products in March 2013 in Figure 4, find the largest gap in quality above 4 (the gap between 5.72 and 6.05) and add a product whose quality is at the midpoint of the gap (5.88). We conduct four simulations where this product is added to Samsung’s,

Figure 4: Quality of Products in March 2013



LG’s, HTC’s or Motorola’s product portfolio, respectively. After Apple, they are the four largest smartphone firms in March 2013 according to their sales in that month. In all four simulations, we choose Sprint, the carrier with the least number of products, as the carrier. The simulation results are presented in Table 8, each column of which represents a different simulation.

Table 8: Welfare Changes when a Product is Added, March 2013 (million \$)

	HTC	LG	Motorola	Samsung
$\Delta(\text{consumer surplus})$	2.43	2.43	2.51	2.79
$\Delta(\text{carrier surplus})$	1.26	1.27	1.29	1.53
$\Delta(\text{smartphone producer variable profits})$	1.04	1.03	1.00	1.64
Lower bound of added fixed costs	2.10	2.11	2.13	2.62

Not surprisingly, consumers are better-off with the additional product in the market (Row 1). Carriers also earn more profits (Row 2). Smartphone firms’ total variable profit increases (Row 3). For the added product, we obtain a lower bound on its fixed cost, which is reported in Row 4 of Table 8. The ratio of the sum of the first three rows to the last is around 2.3 for all four simulations. This implies that as long as the fixed cost is not more than 2.3 times of its estimated lower bound,

the sum of the first three rows minus the fixed cost of the added product (i.e., the change in total welfare) is positive. To put the number 2.3 in perspective, note that the average upper bound and the average lower bound we report in Section 4 are, respectively, 6.16 and 5.17, with a ratio of 1.2. When we replace $\Delta(\text{consumer surplus})$ in Row 1 by that ignoring the change in the Logit error, the ratio becomes around 1.3 (across all four columns), which is still above 1.2.

Overall, our simulation results from removing products and adding a product suggest that there are too few products. As mentioned, there are two countervailing forces: firms do not consider the business-stealing externality, which may lead to excessive product offerings; firms do not consider consumer surplus, which may lead to insufficient product proliferation. Our results suggest that the second effect dominates the first.

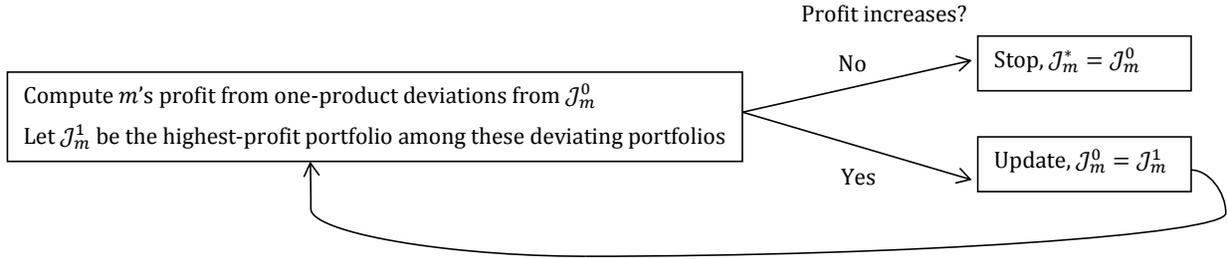
5.2 How does competition affect product offerings?

To study how competition affects product offerings, we simulate the effect of a hypothetical merger between Samsung and LG in March 2013, the second and the third largest smartphone firms in terms of sales in that month, following Apple. In Appendix B, we show the effects of a Samsung-Motorola merger and an LG-Motorola merger, where Motorola is the fourth largest smartphone firm in March 2013. In these merger simulations, we compute the post-merger equilibrium in both product offerings and pricing. In contrast, in Section 5.1, we only need to compute the new pricing equilibrium for given product offerings in the market.

Computing the post-merger product-choice equilibrium can be challenging because the product-choice action space for a firm can be very large. A firm can choose to drop any set of products or add any number of products after the merger. To keep the problem tractable, we restrict the set of potential products for each firm in the merger simulations to be the firm’s products in the data in either March or February 2013, plus two additional potential products that fill gaps in the quality spectrum.²⁰ As shown in the plot of the qualities of products in March 2013 (Figure 4), the quality spectrum exhibits gaps between 5.72 and 6.05 and between 6.40 and 6.64. We find the respective midpoints of these gaps (5.88 and 6.52) and allow each firm to add a product whose quality is either 5.88 or 6.52. These two products can be sold through any of the four carriers in the sample. Products in February or March 2013 are sold through their respective carriers observed in the data. In sum, with this set of potential products, our simulation allows a firm to drop any subset of its existing products, add back any subset of its discontinued products, add one or two additional products, or use a combination of the above three types of adjustments.

²⁰Since we do not have an estimate of the brand effect for the merged Samsung-LG entity, in the merger simulation, we assign the Samsung brand effect to products originally offered by Samsung before the merger, and the LG brand effect to those originally offered by LG. To be consistent, we allow four additional potential products for the merged firm Samsung-LG, two of which carry the Samsung brand effect and two of which carry the LG brand effect. In Appendix C, we repeat the merger simulation by assuming that the post-merger Samsung-LG brand effect is the average of the pre-merger Samsung and LG brand effects. The results are robust to this alternative assumption.

Figure 5: Algorithm for Computing the Best-Response Product Portfolio



Even with this restricted set of potential products, the choice set for a firm can still be too large. This is because a smartphone firm chooses a product portfolio, which is a subset (of any size) of the potential products. In other words, the choice set of a firm is the power set of its potential products. For example, the merged Samsung-LG entity has 31 potential products, and thus a choice set of 2^{31} ($\approx 2.4 \times 10^9$) product portfolios. Moreover, to compute the profit of each product portfolio, we need to compute the corresponding pricing equilibrium, making the computational burden prohibitively high. To address this issue, we use a heuristic algorithm to compute a firm’s optimal product portfolio given its competitors’ product portfolios. This algorithm is then embedded in a best-response iteration to solve for the post-merge product-choice equilibrium.

We use firm m as an example to describe the heuristic algorithm for a firm’s optimal product portfolio problem, and depict the algorithm in Figure 5. Let $\bar{\mathcal{J}}_m$ represent firm m ’s potential products (for example, $\bar{\mathcal{J}}_m = \{j_1, \dots, j_n\}$). We start with a portfolio $\mathcal{J}_m^0 \subseteq \bar{\mathcal{J}}_m$ (for example, $\mathcal{J}_m^0 = \{j_1, \dots, j_{n_1}\}$ where $n_1 \leq n$). We compute firm m ’s profit from each of the following deviations from \mathcal{J}_m^0 : $\mathcal{J}_m^0 \setminus \{j_k\}$, $k = 1, \dots, n_1$ or $\mathcal{J}_m^0 \cup \{j_k\}$, $k = n_1 + 1, \dots, n$. Note that each deviation differs from \mathcal{J}_m^0 in only one product: either a product in \mathcal{J}_m^0 is removed or a potential product not in \mathcal{J}_m^0 is added. Let \mathcal{J}_m^1 be the highest-profit deviating product portfolio. If firm m ’s profit corresponding to \mathcal{J}_m^1 is smaller than that corresponding to \mathcal{J}_m^0 , this procedure stops and returns \mathcal{J}_m^0 as the best response. Otherwise, we compute m ’s profit from any one-product deviation from \mathcal{J}_m^1 by either adding a potential product to or dropping a product from \mathcal{J}_m^1 . We continue this process until firm m ’s profit no longer increases. This algorithm allows us to translate a problem growing exponentially in the number of potential products into one growing linearly in it.²¹

In this algorithm, even though we impose a one-product deviation restriction in each step of the algorithm, the optimal product portfolio found by the algorithm can be very different from the starting portfolio in both product number and composition. This is because each step of the algorithm leads to a one-product deviation and strictly increases profit prior to convergence.

²¹Jeziorski (2014) uses a similar idea to avoid excessive computation burden in studying firm acquisition problems. Specifically, he assumes that when a firm decides on which set of firms to acquire, it makes a sequential decision of whether to acquire each firm according to a pre-specified sequence of potential acquirees. Our algorithm is less restrictive: in each step, a firm evaluates all one-product deviations simultaneously rather than being constrained to one such deviation determined by a pre-specified sequence.

Therefore, as long as the algorithm does not converge after only one step, it yields a product portfolio that deviates from the starting product portfolio by more than one product. Note that product composition can also change as the algorithm drops one product in one step and adds another in a later step.

To evaluate the performance of the algorithm, we conduct Monte Carlo simulations, as discussed in Appendix D. These simulations suggest that our algorithm works well, at least for relatively small problems where we can solve for the true optimal product portfolio without using the heuristic algorithm. Given that we impose a one-product deviation restriction in each step, we also check and confirm that no firm has a two-product profitable deviation at the equilibrium found by the heuristic algorithm in our merger simulations below.

We embed this algorithm in a best-response iteration, where firms take turns updating to their best-response product portfolio. We repeat this iteration until no firm has an incentive to deviate. In the iteration, we loop firms according to their monthly sales in March 2013, either ascending or descending. These two best-response iterations yield the same equilibrium in our merger simulations.

As for fixed costs, we draw the fixed cost for each potential product from a range consistent with the bounds obtained in the estimation and report the average merger effects, averaged over different sets of fixed-cost draws. Specifically, for each product in the data, we have obtained an upper bound of its fixed cost (denoted by \bar{F}_{jt}). For such a product, we randomly draw five fixed-cost values from the range $[0.5\bar{F}_{jt}, \bar{F}_{jt}]$. Similarly, for each potential product not in the data, we have obtained a lower bound of its fixed cost \underline{F}_{jt} . We draw five fixed-cost values from $[\underline{F}_{jt}, 5\underline{F}_{jt}]$. In Appendix C, we consider two alternative ranges for the fixed costs. In one alternative, we fix the length of the range to be $(\bar{F} - \underline{F})$, where $\bar{F} = 6.16$ and $\underline{F} = 5.27$ are the average upper and lower bounds reported in Section 4. In the other alternative, we define the range according to the quality of a product. Our merger simulation results are robust to these two alternative fixed-cost ranges.

Table 9 presents the baseline merger simulation results. These results show an average decrease of 2.50 products after the merger, mainly driven by the merged firm dropping products: the average change for the merged firm is -3.40 while that for the non-merging firms is 0.80. We also find that the merged firm drops products across the quality spectrum except the very top. Specifically, we find that the average number of products dropped from each quality quartile (below the pre-merger 25% quality quantile, [25%, 50%), [50%, 75%), and above 75%) is 0.6, 1, 1, and 0, respectively. Overall, the product variety measure decreases by 21.41 (from 360.25). We use the following back-of-the-envelope calculation to understand the magnitude of such a change. Before the merger, the range of the quality spectrum is 6.68. The pre-merger product variety measure (360.25) is “as if” there are 54.93 equidistant products $(360.25/6.68 + 1)$, while the post-merger product variety

Table 9: The Effect of Samsung-LG Merger, March 2013

	Variable	Pre-merger	Post-merger	Change
(1)	Number of non-flagship products	54	51.40	-2.60
(2)	merged firm	26	22.60	-3.40
(3)	non-merging firms	28	28.80	0.80
(4)	Variety	360.25	338.84	-21.41
(5)	Sales-weighted avg quality	8.40	8.42	0.02
(6)	merged firm	7.32	7.34	0.02
(7)	non-merging firms	6.25	6.25	0.0003
(8)	Sales-weighted avg price (\$)	110.00	111.43	1.42
(9)	merged firm	156.08	164.95	8.87
(10)	non-merging firms	91.23	91.51	0.28
(11)	Total sales	7,002,268	6,914,742	-87,526
(12)	merged firm	2,027,077	1,875,141	-151,936
(13)	non-merging firms	4,975,192	5,039,601	64,410
(14)	Consumer surplus (million \$)	1681.21	1653.10	-28.11
(15)	Carrier profit (million \$)	1266.42	1249.84	-16.58
(16)	Smartphone firm profit (million \$)	1115.45	1128.83	13.39
(17)	merged firm	270.90	272.64	1.74
(18)	non-merging firms	844.55	856.20	11.64

Note: except in Rows (1) - (3), all variables are computed based on all products, including both the flagship products and the non-flagship products.

measure (338.84) is “as if” there are 51.72 equidistant products. Therefore, a change of -21.41 in the product variety measure is equivalent to a decrease of about 3.21 in the number of “as if” equidistant products.

Regarding changes in quality and price, we find little change in the sales-weighted average quality in the market after the merger, but an increase in the sales-weighted average retail price of 1.42 dollars. This is largely due to price increases for the merged firm’s products. Specifically, the results in Row (9) of Table 9 show that the sales-weighted average retail price of the merged firm’s products increases by about 8.87 dollars. Overall, sales for the merged firm decreases and that for the non-merging firms increases, with a net change of -87,526 units. The decrease in product offerings and the increase in prices eventually lead to a reduction in consumer surplus by around 28 million dollars. Carriers are also worse off. The total smartphone profit, however, increases by around 13.39 million dollars, among them, 1.74 million dollars are attributed to the increase in the merged firm’s profit and the remaining 11.64 million dollars are due to changes in non-merging firms’ profits with an average increase of 1.06 million dollars per non-merging firm. Despite the increase in smartphone producer surplus, overall welfare decreases by around 30.84 million dollars.

In summary, the results from this counterfactual simulation show that a reduction in competition leads to a decrease in the number of products across the quality spectrum. This decrease is accompanied by an increase in prices, leading to a decline in consumer and carrier surplus and

eventually a reduction in overall welfare, despite an increase in smartphone producer surplus. Our simulations of other mergers yield similar results (see Appendix B for the Samsung-Motorola and LG-Motorola merger). The combination of our findings in the previous section (i.e., the market contains too few products) and our findings in this section (i.e., a merger further reduces product offerings) suggests that merger policies should be stricter when we take into account the effect of a merger on product offerings.

This conclusion is also consistent with a merger simulation where we keep the set of products fixed and allow firms to adjust only prices after the merger. In such a merger simulation, we find that the changes in consumer surplus, carrier profit, and smartphone firm profit are all smaller (in absolute value). They are -19.46, -10.83 and 8.98 million dollars, respectively. In contrast, they are -28.11, -16.58 and 13.39 million dollars when post-merger adjustments in both product offerings and prices are allowed. The decrease in total surplus is also smaller, again suggesting that the merger policy should be stricter considering firms' endogenous product choice.

6 Robustness Analyses

In this section, we conduct three robustness analyses. We change the demand side of the model in the first two robustness analyses and the supply side in the third. For each robustness analysis, we both re-estimate the model and repeat the counterfactual simulations.

On the demand side, one concern with our discrete choice model is that the assumption of independent idiosyncratic shocks may lead us to overestimate the effect of removing or adding a product on consumer surplus. To address this concern, we conduct two robustness analyses where we add more random coefficients in order to allow greater correlation among the utilities that a consumer gets from different products.

In the first robustness analysis, we add a random coefficient for the Apple dummy variable and allow this random coefficient to be correlated with the quality random coefficient. The estimation results in Table 10(a) indicate that the standard deviation of the Apple-dummy random coefficient is 2.625 and that this random coefficient is highly correlated with the quality random coefficient (the estimated correlation is 0.991). Unfortunately, both estimates are statistically insignificant. For the parameters common to both models, both the estimates and the statistical significance levels are robust. More importantly, the results from the counterfactual simulations, which allow us to address our research questions, are also robust (see Tables 10(b)-(d)). For example, we still find that removing a product reduces total surplus even considering the maximum possible saving in the fixed cost, that adding a product increases total surplus as long as the fixed cost is not much higher than its lower bound and that a merger leads to a reduction in product offerings and eventually a decrease in total welfare.

In the second robustness analysis, we add a random coefficient for each carrier dummy variable.

Table 10: Robustness Analysis: Allowing an Apple Random Coefficient

(a) Estimation Results

	Parameter	Std. Error
Demand		
Quality coefficient		
battery talk time (hours)	0.052***	0.016
camera resolution (megapixel)	0.109***	0.046
chipset generateion 2	0.444***	0.137
chipset generateion 3	0.743***	0.180
chipset generateion 4	1.145***	0.261
chipset generateion 5	1.857***	0.385
screen size (inch)	1	
weight (gram)	-0.002*	0.002
Covariance of random coefficients		
std. dev., quality	0.214**	0.104
std. dev., Apple dummy	2.625	2.248
correlation	0.991	1.559
Price	-0.006	0.079
Apple	0.030	2.059
BlackBerry	1.149***	0.132
Samsung	0.337***	0.069
Flagship?	0.592***	0.069
Carrier/year and quarter dummies		Yes
Marginal Cost (\$)		
Exp(quality/10)	544.583***	2.908
Apple	-252.177***	0.150
BlackBerry	104.275***	0.510
Samsung	-20.101***	0.151
Carrier/year dummies		Yes

*** indicates 99% level of significance.

(b) Welfare Changes when a Product is Removed, March 2013 (million \$)

Removed product	Lowest-quality	Median	Highest
Δ (consumer surplus)	-1.13	-3.14	-7.45
Δ (carrier surplus)	-1.03	-2.08	-4.20
Δ (smartphone producer variable profits)	-0.68	-1.14	-1.89
Upper bound of savings in fixed costs	1.16	2.70	5.82

(c) Welfare Changes when a Product is Added, March 2013 (million \$)

	HTC	LG	Motorola	Samsung
Δ (consumer surplus)	2.67	2.68	2.72	3.18
Δ (carrier surplus)	1.72	1.73	1.75	2.11
Δ (smartphone producer variable profits)	1.20	1.20	1.18	1.85
Lower bound of added fixed costs	2.34	2.35	2.36	2.98

(d) The Effect of Samsung-LG Merger in March 2013

Variable	Pre-merger	Post-merger	Change
Number of non-flagship products	54	46.60	-7.40
Variety	324.84	283.61	-41.23
Sales-weighted avg quality	6.879	6.882	0.003
Sales-weighted avg price (\$)	94.62	99.63	5.01
Total sales	7,398,499	7,190,089	-208,409
Consumer surplus (million \$)	2632.84	2563.01	-69.83
Carrier profit (million \$)	1648.47	1605.85	-42.63
Smartphone firm profit (million \$)	1776.96	1811.47	34.52

The estimation results in Table 11(a) show that the standard deviations of all carrier dummy variable coefficients, except that for T-Mobile, are small and statistically insignificant. The estimates for the parameters common to the two models are robust as are counterfactual simulation results (see Tables 11(b)-(d)).

On the supply side, in the pricing model of the baseline specification, we assume that smartphone firms and carriers make their pricing decisions sequentially: smartphone firms make decisions on wholesale prices before carriers make decisions on retail prices. It is possible that they make the pricing decisions jointly. This is especially likely for Apple and AT&T during the time when they had an exclusive contract (i.e., AT&T was the sole seller for iPhones before February 2011). In the third robustness analysis, we allow Apple and AT&T to set their pre-February 2011 iPhones prices jointly to maximize their joint profit from iPhones.²² Specifically, we take the demand estimates from the baseline model, re-estimate the marginal cost functions and fixed cost bounds and repeat the counterfactual simulations. Our results in Table 12 indicate that our findings remain robust.

In Appendix E, we present the results of additional robustness analyses. First, we consider a model where all smartphone firms and all carriers jointly set retail prices. We also provide a uniform framework following Villas-Boas and Hellerstein (2006) to discuss the differences between the baseline model and these two alternative pricing models. Finally, we show that our results are robust to two additional deviations to the simple linear pricing model.

7 Conclusion

In this paper, we study how oligopolistic competition impacts product offerings in the U.S. smartphone market. To this end, we develop and estimate a model for the demand and supply of smartphones. We first conduct counterfactual simulations where we add or remove products to determine whether there are too few or too many products in the market. We then use merger simulations to study the effects of competition on product offerings, prices, and overall welfare. Our findings show that there are too few products in the market and that a reduction in competition decreases product number and product variety and reduces total welfare. These results suggest that merger policies should be stricter when we take into account the effect of a merger on product choice.

We conclude the paper by highlighting a few caveats of the paper. First, similar to many papers in the endogenous product choice literature, our paper uses a static model to describe consumer demand and firm behavior.²³ On the supply side, this modeling choice is somewhat justifiable as we focus on non-flagship products which presumably do not involve a large sunk cost such as the R&D cost. However, consumers may be dynamic, which will lead to firm dynamic behavior. For

²²At the same time, other carriers choose their retail prices to maximize their profits and AT&T chooses its retail prices for its non-iPhone products to maximize its profit from non-iPhone products.

²³See, for example, Seim (2006), Fan (2013), Eizenberg (2014), and Crawford, Shcherbakov and Shum (2015).

Table 11: Robustness Analysis: Allowing Carrier Random Coefficients

(a) Estimation Results

	Parameter	Std. Error
Demand		
Quality coefficient		
battery talk time (hours)	0.067**	0.032
camera resolution (megapixel)	0.112***	0.043
chipset generation 2	0.456***	0.177
chipset generation 3	0.780***	0.229
chipset generation 4	1.097***	0.275
chipset generation 5	1.786***	0.373
screen size (inch)	1	
weight (gram)	-0.001	0.002
Std. dev. of random coefficients		
quality	0.349*	0.213
AT&T	0.018	23.410
Sprint	0.394	33.860
T-Mobile	4.241**	1.997
Verizon	0.394	33.860
Price	-0.008***	0.003
Apple	2.741***	0.192
BlackBerry	1.253***	0.175
Samsung	0.335***	0.076
Flagship?	0.587***	0.114
Carrier/year and quarter dummies		Yes
Marginal Cost (\$)		
Exp(quality/10)	459.944***	2.816
Apple	-47.073***	0.134
BlackBerry	87.343***	0.521
Samsung	-28.573***	0.148
Carrier/year dummies		Yes

* indicates 90% level of significance. ** indicates 95% level of significance.
*** indicates 99% level of significance.

(b) Welfare Changes when a Product is Removed, March 2013 (million \$)

Removed product	Lowest-quality	Median	Highest
Δ (consumer surplus)	-0.99	-2.39	-10.54
Δ (carrier surplus)	-1.15	-1.40	-10.38
Δ (smartphone producer variable profits)	-0.12	-0.66	-0.56
Upper bound of savings in fixed costs	0.96	2.05	10.42

(c) Welfare Changes when a Product is Added, March 2013 (million \$)

	HTC	LG	Motorola	Samsung
Δ (consumer surplus)	1.96	1.92	2.03	2.44
Δ (carrier surplus)	0.95	0.95	0.99	1.26
Δ (smartphone producer variable profits)	0.8	0.81	0.77	1.34
Lower bound of added fixed costs	1.62	1.61	1.66	2.18

(d) The Effect of Samsung-LG Merger in March 2013

Variable	Pre-merger	Post-merger	Change
Number of non-flagship products	54	28.80	-25.20
Variety	379.09	232.45	-146.64
Sales-weighted avg quality	8.38	8.44	0.05
Sales-weighted avg price (\$)	94.71	102.50	7.80
Total sales	7,893,045	7,697,927	-195,118
Consumer surplus (million \$)	2230.96	2171.69	-59.26
Carrier profit (million \$)	1577.60	1559.69	-17.91
Smartphone firm profit (million \$)	1299.89	1376.39	76.51

Table 12: Robustness Analysis: Apple and AT&T Joint Price Setting before February 2011

(a) Estimation Results of Marginal Cost Parameters

	Parameter	Std. Error
Exp(quality/10)	460.828***	2.274
Apple	6.473***	0.107
BlackBerry	86.426***	0.393
Samsung	-17.546***	0.119
Carrier/year dummies	Yes	

*** indicates 99% level of significance.

(b) Welfare Changes when a Product is Removed, March 2013 (million \$)

Removed product	Lowest-quality	Median	Highest
Δ (consumer surplus)	-0.80	-2.59	-14.08
Δ (carrier surplus)	-0.72	-1.43	-10.22
Δ (smartphone producer variable profits)	-0.47	-1.00	-4.22
Upper bound of savings in fixed costs	0.83	2.29	13.93

(c) Welfare Changes when a Product is Added, March 2013 (million \$)

	HTC	LG	Motorola	Samsung
Δ (consumer surplus)	2.41	2.41	2.49	2.61
Δ (carrier surplus)	1.26	1.27	1.29	1.44
Δ (smartphone producer variable profits)	1.11	1.11	1.08	1.66
Lower bound of added fixed costs	2.13	2.14	2.17	2.52

(d) The Effect of Samsung-LG Merger in March 2013

Variable	Pre-merger	Post-merger	Change
Number of non-flagship products	54	51.60	-2.40
Variety	360.25	339.96	-20.29
Sales-weighted avg quality	8.34	8.36	0.02
Sales-weighted avg price (\$)	128.08	130.32	2.24
Total sales	6,792,576	6,697,845	-94,731
Consumer surplus (million \$)	1632.88	1602.54	-30.34
Carrier profit (million \$)	1225.29	1208.31	-16.97
Smartphone firm profit (million \$)	1044.85	1058.08	13.23

example, it may be costly for consumers to switch from one carrier to another. Given such frictions, firms may consider how their decisions in the current period affect their payoffs in the future. Note that, in a reduced-form way, our carrier/year fixed effects in the utility function capture an average switching cost.²⁴ Similarly, our estimated fixed cost in a reduced-form way captures both the true fixed cost and the effect of a product on future firm profits. That said, we acknowledge that we keep the carrier/year fixed effect and the fixed cost constant in the counterfactual simulations and therefore do not discuss industry dynamics.

Second, our model does not explain the choice of a carrier by a smartphone firm. As a result, we do not discuss the effect of competition on the carrier choice for each product, which may affect the pricing equilibrium, and thus a smartphone firm's product offerings. We could expand our

²⁴For instance, the fixed effect for Verizon in a year captures its opponents' market shares in the previous year, which determines the proportion of consumers who have to pay switching costs to buy a Verizon product this year. Therefore, this fixed effect somewhat captures the average switching cost for consumers to buy a Verizon product.

definition of potential products for each firm to allow firms to choose carriers.²⁵ However, given that doing so increases the computational burden substantially and that in the data, we do not observe smartphone firms moving one product from one carrier to another, we leave this for future research.

References

Berry, Steven, Alon Eizenberg, and Joel Waldfogel (forthcoming), “Horizontal and vertical product variety in radio markets.” *RAND Journal of Economics*.

Berry, Steven, James Levinsohn, and Ariel Pakes (1995), “Automobile prices in market equilibrium.” *Econometrica*, 63, 841–90.

Chu, Chenghuan Sean (2010), “The effect of satellite entry on cable television prices and product quality.” *RAND Journal of Economics*, 41, 730–764.

Crawford, Gregory (2012), “Accommodating endogenous product choices: A progress report.” *International Journal of Industrial Organization*, 30, 315–320.

Crawford, Gregory S., Oleksandr Shcherbakov, and Matthew Shum (2015), “The welfare effects of endogenous quality choice in cable television markets.” Cepr discussion paper.

Crawford, Gregory S. and Ali Yurukoglu (2012), “The Welfare Effects of Bundling in Multichannel Television Markets.” *American Economic Review*, 102, 643–85.

Draganska, Michaela, Michael Mazzeo, and Katja Seim (2009), “Beyond plain vanilla: Modeling joint product assortment and pricing decisions.” *Quantitative Marketing and Economics*, 7, 105–146.

Eizenberg, Alon (2014), “Upstream innovation and product variety in the U.S. home PC market.” *Review of Economic Studies*, 81, 1003–1045.

Fan, Ying (2013), “Ownership Consolidation and Product Characteristics: A Study of the US Daily Newspaper Market.” *American Economic Review*, 103, 1598–1628.

Gartner, Inc. (2007), *Gartner Smart Phone Marketshare*.

Gartner, Inc. (2015), *Gartner Smart Phone Marketshare*.

GfK (2016), *Global smartphone sales hit a quarterly high in Q4 2015*.

²⁵For example, we could add the combination of a firm’s products in March 2013 with all carriers as additional potential products for the firm.

- Jeziorski, Przemyslaw (2014), “Estimation of cost efficiencies from mergers: application to US radio.” *RAND Journal of Economics*, 45, 816–846.
- Johnson, Justin P. and David P. Myatt (2003), “Multiproduct Quality Competition: Fighting Brands and Product Line Pruning.” *American Economic Review*, 93, 748–774.
- Luo, Rong (2015), “The operating system network effect and carriers’ dynamic pricing of smartphones.” working paper, University of Georgia.
- Mankiw, N. Gregory and Michael Whinston (1986), “Free entry and social inefficiency.” *RAND Journal of Economics*, 17, 48–58.
- Nosko, Chris (2014), “Competition and quality choice in the cpu market.” working paper, University of Chicago.
- Orhun, Yesim, Sriram Venkataraman, and Pradeep Chintagunta (2015), “Impact of competition on product decisions: Movie choices of exhibitors.” *Marketing Science*, 35, 73–92.
- Seim, Katja (2006), “An empirical model of firm entry with endogenous product-type choices.” *RAND Journal of Economics*, 37, 619–640.
- Shen, Jian, Huanxing Yang, and Lixin Ye (2016), “Competitive nonlinear pricing and contract variety.” *The Journal of Industrial Economics*, 64, 64–108.
- Sinkinson, Michael (2014), “Pricing and entry incentives with exclusive contracts: Evidence from smartphones.” working paper, University of Pennsylvania.
- Sweeting, Andrew (2013), “Dynamic product positioning in differentiated product markets: The effect of fees for musical performance rights on the commercial radio industry.” *Econometrica*, 81, 1763–1803.
- Thomas, Catherine (2011), “Too many products: Decentralized decision making in multinational firms.” *American Economic Journal: Microeconomics*, 3, 280–306.
- Villas-Boas, Sofia and Rebecca Hellerstein (2006), “Identification of supply models of retailer and manufacturer oligopoly pricing.” *Economics Letters*, 90, 132–140.
- Watson, Randal (2009), “Product variety and competition in the retail market for eyeglasses.” *Journal of Industrial Economics*, 57, 217–251.
- Wollmann, Thomas (2016), “Trucks without bailouts: Equilibrium product characteristics for commercial vehicles.” working paper, University of Chicago.

Yang, Chenyu (2016), “Does vertical integration increase innovation?” working paper, University of Michigan.

Zhu, Ting, Hongju Liu, and Pradeep K. Chintagunta (2015), “Wireless carriers’ exclusive handset arrangements: An empirical look at the iphone.” *Customer Needs and Solutions*, 2, 177–190.

Appendices

A List of Flagship Smartphones

Flagship Products (2009/01 – 2013/03)

Brand	Model	Brand	Model	
HTC	G1	Apple	iPhone 3G	
	myTouch 3G		iPhone 3G	
	Hero		iPhone 4	
	myTouch 4G		iPhone 4s	
	Desire HD		iPhone 5	
	Evo 3D	BlackBerry	88XX	
	Sensation		Curve	
	One X		Storm	
	Droid DNA		Bold	
	Windows Phone 8X		Torch	
LG	Optimus One	Bold Touch		
	Optimus 2X	BlackBerry 10		
	Optimus G	Nokia	Lumia 900	
Motorola	Droid		Lumia 920	
	Droid X		Samsung	Galaxy S
	Atrix 4G			Galaxy S II
	Droid Bionic			Galaxy S III
	Droid Razr			Galaxy Note II
	Droid Razr Maxx			
Droid Razr M				

B Additional Merger Simulations

In Section 5, we have shown the simulation result for a merger between Samsung and LG in March 2013, the second and third largest firms in terms of sales in that month. In this section, we conduct two additional merger simulations: a Samsung-Motorola merger (a merger between the second-largest and the fourth-largest firms) and an LG-Motorola merger (a merger between the third-largest and the fourth-largest firms). The simulation results are presented in Table B.1. A

Table B.1: Results from Additional Merger Simulations, March 2013

Variable	Pre-merger	Post-merger	Change
The Samsung-Motorola Merger			
(1) Number of non-flagship products	54	52.60	-1.40
(2) merged firm	20	18.40	-1.60
(3) non-merging firms	34	34.20	0.20
(4) Variety	360.25	355.83	-4.42
(5) Sales-weighted avg quality	8.401	8.416	0.014
(6) merged firm	7.359	7.364	0.005
(7) non-merging firms	6.245	6.256	0.001
(8) Sales-weighted avg price (\$)	110.00	110.68	0.68
(9) merged firm	161.32	167.08	5.76
(10) non-merging firms	89.91	90.14	0.23
(11) Total sales	7,002,268	6,933,248	-69,020
(12) merged firm	1,970,008	1,851,104	-118,904
(13) non-merging firms	5,032,261	5,082,144	49,883
(14) Consumer surplus (million \$)	1681.21	1658.65	-22.57
(15) Carrier profit (million \$)	1266.42	1250.16	-16.26
(16) Smartphone firm profit (million \$)	1115.45	1127.95	12.50
(17) merged firm	274.71	276.30	1.59
(18) non-merging firms	840.74	851.64	10.91
The LG-Motorola Merger			
(1) Number of non-flagship products	54	53.60	-0.40
(2) merged firm	16	15.60	-0.40
(3) non-merging firms	38	38.00	0
(4) Variety	360.25	358.39	-1.86
(5) Sales-weighted avg quality	8.401	8.406	0.005
(6) merged firm	7.106	7.104	-0.002
(7) non-merging firms	6.495	6.495	0.0002
(8) Sales-weighted avg price (\$)	110.00	110.34	0.34
(9) merged firm	144.92	149.02	4.10
(10) non-merging firms	105.99	106.10	0.11
(11) Total sales	7,002,268	6,984,189	-18,079
(12) merged firm	721,570	690,466	-31,103
(13) non-merging firms	6,280,699	6,293,722	13,024
(14) Consumer surplus (million \$)	1681.21	1675.47	-5.74
(15) Carrier profit (million \$)	1266.42	1262.39	-4.03
(16) Smartphone firm profit (million \$)	1115.45	1119.01	3.56
(17) merged firm	59.29	59.51	0.22
(18) non-merging firms	1056.16	1059.50	3.34

comparison of the results in Table 9 for the Samsung-LG merger to the results here shows that, not surprisingly, the merger effects on product offerings and welfare are smaller for mergers between smaller firms. However, the qualitative findings are robust. Specifically, we find that all three mergers lead to a decrease in product variety. In terms of welfare, all three mergers result in a decrease in both consumer and carrier surplus, but an increase in smartphone producer surplus. The overall welfare effect is always negative.

C Merger Simulations with Different Specifications

In this section, we repeat the Samsung-LG merger simulation with two variations. In the first variation, we use a different assumption on the post-merger brand effect for the merged firm. In the second variation, we use different ranges for the fixed cost draws.

As mentioned in Footnote 20, for the merger simulation in Section 5, we assign the Samsung brand effect to products originally offered by Samsung before the merger and the LG brand effect to those originally offered by LG. In this section, we repeat the merger simulation under the assumption that the post-merger Samsung-LG brand effect is the average of the pre-merger Samsung brand effect and the LG brand effect. The results in Table C.2 show that our main findings are robust to this new assumption. Note that the merged firm’s profit now decreases after a merger (instead of increases, as in the baseline specification) because the original Samsung products now have a smaller brand effect.

Table C.2: Samsung-LG Simulation Results using the Average Brand Effect for the Merged Firm

	Variable	Pre-merger	Post-merger	Change
(1)	Number of non-flagship products	54	48.40	-5.60
(2)	merged firm	26	19.20	-6.80
(3)	non-merging firms	28	29.20	1.20
(4)	Variety	360.25	342.76	-17.48
(5)	Sales-weighted avg quality	8.40	8.46	0.06
(6)	merged firm	7.32	7.50	0.18
(7)	non-merging firms	6.247	6.240	0.001
(8)	Sales-weighted avg price (\$)	110.00	115.04	5.03
(9)	merged firm	156.08	182.97	26.89
(10)	non-merging firms	91.23	91.85	0.62
(11)	Total sales	7,002,268	6,823,507	-178,761
(12)	merged firm	2,027,077	1,737,962	-289,115
(13)	non-merging firms	4,975,192	5,085,545	110,354
(14)	Consumer surplus (million \$)	1681.21	1628.63	-52.58
(15)	Carrier profit (million \$)	1266.42	1231.88	-34.54
(16)	Smartphone firm profit (million \$)	1115.45	1136.21	20.76
(17)	merged firm	270.90	269.58	-1.32
(18)	non-merging firms	844.55	866.63	22.08

Turning to the second variation, note that in Section 5, we draw fixed costs from $[0.5\bar{F}_{jt}, \bar{F}_{jt}]$ for a product in the data and from $[\underline{F}_{jt}, 5\underline{F}_{jt}]$ for a potential product not in the data. In this section, we consider two different ranges for the fixed costs:

- (1) $[\bar{F}_{jt} - (\bar{F} - \underline{F}), \bar{F}_{jt}]$ for a product in the data and $[\underline{F}_{jt}, \underline{F}_{jt} + (\bar{F} - \underline{F})]$ for a potential product not in the data, where $\bar{F} = 6.16$ and $\underline{F} = 5.27$ are, respectively, the average upper bound and the average lower bound reported in Section 4.
- (2) $[\bar{F}_{jt} - (L_u(q_{jt}) - L_l(q_{jt})), \bar{F}_{jt}]$ for a product in the data and $[\underline{F}_{jt}, \underline{F}_{jt} + (L_u(q_{jt}) - L_l(q_{jt}))]$ for a potential product not in the data, where $L_u(q_{jt}) = \hat{b}_{u0} + \hat{b}_{u1}q_{jt}$ and $(\hat{b}_{u0}, \hat{b}_{u1})$ are obtained by regressing the upper bounds reported in Section 4 on quality, and $L_l(q_{jt})$ is analogously defined using the lower bounds reported.

Note that with both alternatives, the ranges are well-defined, i.e., the distance of the range is always non-negative. In Table C.3, we show that the simulation results presented in Section 5 are robust to these two alternative fixed-cost ranges.

D Monte Carlo Test of the Heuristic Algorithm

In this section, we conduct Monte Carlo simulations to evaluate the performance of the heuristic algorithm explained in Section 5. To this end, we study product-choice problems where the number of potential products is small enough for us to find the optimal product portfolio without using the algorithm. We evaluate the performance of the algorithm by comparing the optimal product portfolio determined by the algorithm to the true optimal product portfolio.

To construct these Monte Carlo simulations, we first randomly draw K products from Samsung's non-flagship products in March 2013. For each of these K products, we compute the variable profit if this product were the only product in the market. We then draw a K -by-1 vector of fixed costs uniformly from an interval between 0 and the maximum of the K variable profits.²⁶ Given these fixed-cost draws, we compute the firm profit (variable profit less the fixed cost) corresponding to each of the 2^K possible product portfolios to find the most profitable one. We also use the heuristic algorithm to search for the profit-maximizing portfolio and record the outcome obtained from using each of the 2^K product portfolios as the starting point for the algorithm. We conduct such a simulation 100×500 times, where 100 is the number of draws for the K potential products and 500 is the number of draws for the K fixed costs. Finally, we compute the failure rate (i.e., the number of simulations where the heuristic algorithm fails to find the true optimal product portfolio/50,000), separately for every starting point.

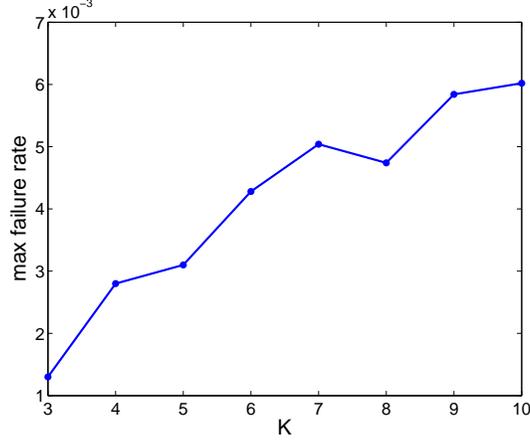
²⁶We do not use the bounds obtained in the estimation results section (Section 4.2) for this exercise because K in this exercise is much smaller than the number of products in the data. As a result, the change in variable profit from adding or removing a product in this exercise is larger than that in Section 4.2. If we were to use the bounds reported there, we would find, in this exercise, that it is always optimal to have all K products in the market.

Table C.3: Samsung-LG Simulation Results using Different Ranges for Fixed-cost Draws

Variable	Pre-merger	Post-merger	Change
Alternative Fixed-cost Range (1)			
(1) Number of non-flagship products	54	51.40	-2.60
(2) merged firm	26	20.40	-5.60
(3) non-merging firms	28	31.00	3.00
(4) Variety	360.25	342.12	-18.12
(5) Sales-weighted avg quality	8.40	8.42	0.02
(6) merged firm	7.32	7.36	0.04
(7) non-merging firms	6.247	6.244	-0.003
(8) Sales-weighted avg price (\$)	110.00	109.81	-0.19
(9) merged firm	156.08	164.70	8.62
(10) non-merging firms	91.23	90.51	-0.72
(11) Total sales	7,002,268	6,902,622	-99,647
(12) merged firm	2,027,077	1,795,937	-231,140
(13) non-merging firms	4,975,192	5,106,685	131,493
(14) Consumer surplus (million \$)	1681.21	1648.02	-33.19
(15) Carrier profit (million \$)	1266.42	1248.00	-18.42
(16) Smartphone firm profit (million \$)	1081.49	1097.74	16.25
(17) merged firm	252.58	254.81	2.23
(18) non-merging firms	828.91	842.94	14.02
Alternative Fixed-cost Range (2)			
(1) Number of non-flagship products	54	51.60	-2.40
(2) merged firm	26	20.80	-5.20
(3) non-merging firms	28	30.80	2.80
(4) Variety	360.25	341.57	-18.67
(5) Sales-weighted avg quality	8.40	8.42	0.02
(6) merged firm	7.32	7.37	0.04
(7) non-merging firms	6.247	6.244	-0.003
(8) Sales-weighted avg price (\$)	110.00	110.48	0.47
(9) merged firm	156.08	166.44	10.36
(10) non-merging firms	91.23	90.65	-0.58
(11) Total sales	7,002,268	6,904,168	-98,101
(12) merged firm	2,027,077	1,806,983	-220,094
(13) non-merging firms	4,975,192	5,097,185	121,993
(14) Consumer surplus (million \$)	1681.21	1648.93	-32.29
(15) Carrier profit (million \$)	1266.42	1248.81	-17.61
(16) Smartphone firm profit (million \$)	1084.84	1099.96	15.12
(17) merged firm	254.18	256.13	1.95
(18) non-merging firms	830.65	843.83	13.18

We repeat the above Monte Carlo simulations for the numbers of potential products $K = 3, \dots, 10$. In Figure D.1, for each of these Monte Carlo studies where K varies between 3 and 10, we plot the maximum failure rate across all 2^K starting points. Figure D.1 shows that, as the number of potential products (K) increases, so does the maximum failure rate.²⁷ However, it is smaller than 0.61% even for $K = 10$. This result indicates that the heuristic algorithm works well at least for a relatively small optimal product-choice problem.

Figure D.1: Failure Rate of the Heuristic Algorithm



E Additional Robustness Analyses

We have shown in Section 6 that our results are robust to an alternative pricing model, where Apple and AT&T jointly set the retail prices for iPhones before their exclusive contract expired. In this section, we conduct three additional robustness analyses regarding the supply side of the model.

Note that the simple linear pricing model in the baseline specification implies that there exists a double marginalization as follows:

$$\mathbf{p} = (-\Gamma_c \circ \Delta_c)^{-1} \mathbf{s} + (-\Gamma_m \circ \Delta_m)^{-1} \mathbf{s} + \tilde{\mathbf{m}}\mathbf{c}, \quad (\text{E.1})$$

where the operator \circ represents the element-wise multiplicity, and Γ_c is a matrix whose (i, j) element = 1 if products i and j are sold by the same carrier, and 0 otherwise. Analogously, Γ_m is a matrix whose (i, j) element = 1 if and only if products i and j are produced by the same smartphone firm. While Γ_c and Γ_m describe the “ownership,” the other two matrices, Δ_c and Δ_m , describe the price sensitivity of demand. Specifically, the (i, j) element of Δ_c and Δ_m are, respectively, $\frac{\partial s_j}{\partial p_i}$ and $\sum_k \frac{\partial s_j}{\partial p_k} \frac{\partial p_k^*}{\partial w_i}$.

As pointed out by Villas-Boas and Hellerstein (2006), it is possible that the pricing strategies of smartphone firms and/or carriers deviate from a linear pricing model. Villas-Boas and Hellerstein

²⁷Given the finite number of simulation draws, the dip at $K = 8$ may be explained by simulation errors.

(2006) introduce two vectors Λ_c and Λ_m to capture such deviations so that the following equation describes the pricing behavior:

$$\mathbf{p} = \left[(-\bar{\Gamma}_c \Delta_c)^{-1} \mathbf{s} \right] \circ \Lambda_c + \left[(-\bar{\Gamma}_m \Delta_m)^{-1} \mathbf{s} \right] \circ \Lambda_m + \tilde{\mathbf{m}} \mathbf{c}, \quad (\text{E.2})$$

where the “ownership” matrices $\bar{\Gamma}_c$ and $\bar{\Gamma}_m$ can also deviate from those in the simple linear pricing model (i.e., Γ_c and Γ_m).

The baseline model is a case where Λ_c and Λ_m are both constant-1 vectors and $\bar{\Gamma}_c = \Gamma_c$ and $\bar{\Gamma}_m = \Gamma_m$. With a slight abuse of notation, we refer to this case as ($\Lambda_c = 1, \Lambda_m = 1, \bar{\Gamma}_c = \Gamma_c, \bar{\Gamma}_m = \Gamma_m$). The Apple and AT&T joint price setting model we studied in Section 6 is a case where $\Lambda_c = 1, \bar{\Gamma}_m = \Gamma_m$, and

$$\Lambda_m(j) = \begin{cases} 1 & \text{if } j \in \text{non-Apple} \\ 0 & \text{otherwise} \end{cases} \quad (\text{E.3})$$

$$\bar{\Gamma}_c(i, j) = \begin{cases} 1 & \text{if } i, j \in (\text{iPhones}) \text{ or } (\text{AT\&T and non-iPhones}) \text{ or } (\text{same non-AT\&T carrier}) \\ 0 & \text{otherwise.} \end{cases}$$

We now consider three alternative deviations from the baseline model:

(1) ($\Lambda_c = 0, \Lambda_m = 1, \bar{\Gamma}_c = \Gamma_c, \bar{\Gamma}_m = \Gamma_m$)²⁸

(2) ($\Lambda_c = 1, \Lambda_m = 0, \bar{\Gamma}_c = \Gamma_c, \bar{\Gamma}_m = \Gamma_m$)

(3) All smartphones and all carriers jointly set retail prices. Specifically, we consider each smartphone firm/carrier pair (m, c) to jointly solve the following maximization problem:

$$\max_{p_j, j \in \mathcal{J}_{mc}} \underbrace{\sum_{j \in \mathcal{J}_{mc}} \pi_j(\mathbf{p})}_{\text{pair } (m,c)\text{'s profit}} + \underbrace{\mu_m \sum_{j \in \mathcal{J}_m, j \notin \mathcal{J}_c} \tau \pi_j(\mathbf{p})}_{\text{firm } m\text{'s profit from other products}} + \underbrace{\mu_c \sum_{j \in \mathcal{J}_c, j \notin \mathcal{J}_m} (1 - \tau) \pi_j(\mathbf{p})}_{\text{carrier } c\text{'s profit from other products}}, \quad (\text{E.4})$$

where $\pi_j(\mathbf{p}) = (p_j - \tilde{m}c_j) s_j(\mathbf{p})$ is the profit from selling product j , the parameter τ is the share of profit that goes to a smartphone firm (and thus $1 - \tau$ is the share for a carrier), and μ_m and μ_c are, respectively, the weights that the smartphone firm/carrier pair puts on the smartphone firm’s profit from selling other products and the carrier’s profit from selling other products. This model is therefore equivalent to $\Lambda_c = 1, \Lambda_m = 0$, and

$$\bar{\Gamma}_c(i, j) = \begin{cases} 1 & \text{if } i, j \in \text{same smartphone firm/carrier} \\ \mu_m \tau & \text{if } i, j \in \text{same smartphone firms, but different carriers} \\ \mu_c (1 - \tau) & \text{if } i, j \in \text{same carrier, but different smartphone firms} \\ 0 & \text{otherwise.} \end{cases} \quad (\text{E.5})$$

²⁸In this case, the (i, j) element of Δ_m is $\frac{\partial s_j}{\partial p_i}$.

For all three robustness analyses, we re-estimate the marginal cost parameters and the bounds on the fixed costs and repeat our counterfactual simulations. In what follows, we suppress the subscript “t” and ignore the distinction between j and \tilde{j} for simplicity of exposition.

E.1 The case of $(\Lambda_c = 0, \Lambda_m = 1, \bar{\Gamma}_m = \Gamma_m)$

In this case, there may be a transfer from a smartphone firm to a carrier. Let T_m be the total transfer that a smartphone firm m pays, $T_{m,\setminus j}$ be the transfer when product j is removed from m 's product portfolio and $T_{m,\cup j}$ be the transfer when product j is added to m 's product portfolio. Then, the two inequalities (11) and (12) in Section 3, which capture the optimal conditions for m 's product choice in the baseline model, become:

$$\begin{aligned} E_{(\xi,\eta)}\pi_m(\mathbf{q}, \xi, \eta) - F_j - T_m &\geq E_{(\xi,\eta)}\pi_m(\mathbf{q}\setminus q_j, \xi\setminus\xi_j, \eta\setminus\eta_j) - T_{m,\setminus j} \text{ for any } j \in \mathcal{J}_m & \text{(E.6)} \\ E_{(\xi,\eta)}\pi_m(\mathbf{q}, \xi, \eta) - T_m &\geq E_{(\xi,\eta)}\pi_m(\mathbf{q} \cup q_j, \xi \cup \xi_j, \eta \cup \eta_j) - F_j - T_{m,\cup j} \text{ for any } j \notin \mathcal{J}_m. \end{aligned}$$

The two inequalities in (E.6) imply that for any $j \in \mathcal{J}_m$,

$$\begin{aligned} F_j &\leq [E_{(\xi,\eta)}\pi_m(\mathbf{q}, \xi, \eta) - E_{(\xi,\eta)}\pi_m(\mathbf{q}\setminus q_j, \xi\setminus\xi_j, \eta\setminus\eta_j)] - [T_m - T_{m,\setminus j}] & \text{(E.7)} \\ &\triangleq \Delta\pi_{m,\setminus j} - [T_m - T_{m,\setminus j}] \triangleq \bar{F}_j, \end{aligned}$$

and for any $j \notin \mathcal{J}_m$,

$$\begin{aligned} F_j &\geq [E_{(\xi,\eta)}\pi_m(\mathbf{q} \cup q_j, \xi \cup \xi_j, \eta \cup \eta_j) - E_{(\xi,\eta)}\pi_m(\mathbf{q}, \xi, \eta)] - [T_{m,\cup j} - T_m] & \text{(E.8)} \\ &\triangleq \Delta\pi_{m,\cup j} - [T_m - T_{m,\cup j}] \triangleq \underline{F}_j. \end{aligned}$$

Under the assumption that the total transfer that a smartphone pays at least weakly increases with the number of its products, i.e., $T_m - T_{m,\setminus j} \geq 0$ and $T_{m,\cup j} - T_m \geq 0$, we have $\bar{F}_j \leq \Delta\pi_{m,\setminus j}$ and $\underline{F}_j \leq \Delta\pi_{m,\cup j}$. In Table E.4 where we present the simulation results when a product is removed or added, we report $\Delta\pi_{m,\setminus j}$ as the upper bound of the saving in fixed costs, and $\Delta\pi_{m,\cup j}$ as the lower bound. In doing so, we overestimate both bounds. Nonetheless, from Table E.4, we can see that, even with such an overestimation, our results are robust: removing a product leads to a decrease in total welfare even considering the (over-estimated) maximum possible saving in the fixed cost while adding a product leads to an increase in the total welfare as long as the fixed cost of the added product is not much higher than its (over-estimated) lower bound. In sum, our results on welfare changes when a product is added or removed are robust to this change to the supply side of the model.²⁹

²⁹We do not conduct robustness analyses regarding the merger simulations because doing so requires us to make assumptions on how large the transfer from each smartphone firm to each carrier is and how a merger affects the transfers between smartphone firms and carriers.

Table E.4: Robustness Test, $\Lambda_c = 0, \Lambda_m = 1$

(a) Welfare Changes when a Product is Removed, March 2013 (million \$)

Removed product	Lowest-quality	Median	Highest
$\Delta(\text{consumer surplus})$	-1.03	-2.28	-13.98
$\Delta(\text{total producer surplus net of fixed costs})^a$	-0.59	-0.83	-3.93
$\Delta\pi_{m,\setminus j}$	0.97	2.03	12.17

^aThe sum of carriers' variable profits and smartphone firms' variable profits.

(b) Welfare Changes when a Product is Added, March 2013 (million \$)

	HTC	LG	Motorola	Samsung
$\Delta(\text{consumer surplus})$	2.35	2.40	2.40	2.71
$\Delta(\text{total producer surplus net of fixed costs})$	1.02	0.99	0.99	1.69
$\Delta\pi_{m,\cup j}$	2.14	2.17	2.17	2.70

E.2 The case of ($\Lambda_c = 1, \Lambda_m = 0, \bar{\Gamma}_c = \Gamma_c$)

Similarly, in this case, there is a transfer from a carrier to a smartphone. Let T_m be the total transfer that a smartphone firm m receives, and $T_{m,\setminus j}$ and $T_{m,\cup j}$ be that when j is removed from or when j is added to m 's product portfolio. Then, the two inequalities (11) and (12) become:

$$T_m - F_j \geq T_{m,\setminus j} \iff F_j \leq T_m - T_{m,\setminus j} \text{ for any } j \in \mathcal{J}_m \quad (\text{E.9})$$

$$T_m \geq T_{m,\cup j} - F_j \iff F_j \geq T_{m,\cup j} - T_m \text{ for any } j \notin \mathcal{J}_m. \quad (\text{E.10})$$

In Table E.5, which presents the simulation results in this robustness analysis, we report the changes in the (pre-transfer) profit of j 's carrier as the bounds, i.e., $\Delta\pi_{c,\setminus j} = E_{(\xi,\eta)}\pi_c(\mathbf{q}, \xi, \eta) - E_{(\xi,\eta)}\pi_c(\mathbf{q}\setminus q_j, \xi\setminus\xi_j, \eta\setminus\eta_j)$ or $\Delta\pi_{c,\cup j} = E_{(\xi,\eta)}\pi_c(\mathbf{q} \cup q_j, \xi \cup \xi_j, \eta \cup \eta_j) - E_{(\xi,\eta)}\pi_c(\mathbf{q}, \xi, \eta)$. Under the assumption that, when a product is added, the increase in the amount of transfer that the smartphone firm receives is not larger than the increase in the carrier's (pre-transfer) profit (i.e., $T_m - T_{m,\setminus j} \leq \Delta\pi_{c,\setminus j}$ and $T_{m,\cup j} - T_m \leq \Delta\pi_{c,\cup j}$), the bounds of the fixed cost reported in Table E.5 are again over estimated. Therefore, from Table E.5, we draw a similar robustness conclusion as in the case of ($\Lambda_c = 0, \Lambda_m = 1$).

E.3 The case of smartphone firm/carrier joint price setting

We consider two different choices of (μ_c, μ_m, τ) in (E.4) and report the results in Table E.6. The results are again robust.

Table E.5: Robustness Test, $\Lambda_c = 1, \Lambda_m = 0$

(a) Welfare Changes when a Product is Removed, March 2013 (million \$)

Removed product	Lowest-quality	Median	Highest
$\Delta(\text{consumer surplus})$	-0.82	-2.19	-10.65
$\Delta(\text{total producer surplus net of fixed costs})$	-0.74	-1.14	-7.63
$\Delta\pi_{c,\setminus j}$	0.91	2.10	11.81

(b) Welfare Changes when a Product is Added, March 2013 (million \$)

	HTC	LG	Motorola	Samsung
$\Delta(\text{consumer surplus})$	2.19	2.19	2.19	2.76
$\Delta(\text{total producer surplus net of fixed costs})$	1.06	1.06	1.06	1.42
$\Delta\pi_{c,\cup j}$	2.82	1.72	1.72	4.38

Table E.6: Robustness Test: Smartphone Firm/Carrier Pairs Joint Price Setting

(a) ($\mu_c = 0, \mu_m = 0$)^a

(a.1) Welfare Changes when a Product is Removed, March 2013 (million \$)

Removed product	Lowest-quality	Median	Highest
$\Delta(\text{consumer surplus})$	-0.85	-1.87	-10.93
$\Delta(\text{total producer surplus net of fixed costs})$	-0.56	-0.86	-4.60
Upper bound of savings in fixed costs	0.41	0.87	5.26

(a.2) Welfare Changes when a Product is Added, March 2013 (million \$)

	HTC	LG	Motorola	Samsung
$\Delta(\text{consumer surplus})$	1.94	1.93	1.96	2.50
$\Delta(\text{total producer surplus net of fixed costs})$	0.96	0.96	0.96	1.34
Lower bound of added fixed costs	0.90	0.91	0.91	1.08

^aIn this case, the value of τ is irrelevant.(b) ($\mu_c = 0.5, \mu_m = 0.5, \tau = 0.5$)

(b.1) Welfare Changes when a Product is Removed, March 2013 (million \$)

Removed product	Lowest-quality	Median	Highest
$\Delta(\text{consumer surplus})$	-0.82	-1.90	-10.90
$\Delta(\text{total producer surplus net of fixed costs})$	-0.58	-0.88	-4.98
Upper bound of savings in fixed costs	0.42	0.91	5.56

(b.2) Welfare Changes when a Product is Added, March 2013 (million \$)

	HTC	LG	Motorola	Samsung
$\Delta(\text{consumer surplus})$	1.95	1.96	1.97	2.43
$\Delta(\text{total producer surplus net of fixed costs})$	0.96	0.96	0.96	1.38
Lower bound of added fixed costs	0.91	0.93	0.92	1.11