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

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December 23, 2017
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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 that this market contains too few products and that a reduction in competition decreases both the number and variety of products. These results suggest that product choice adjustment may exacerbate the welfare effect of a merger.

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 the level of 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 too few or too many products. On the one hand, because firms do not take into account the business

*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 many seminars 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.
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stealing externality, there may be too many products. On the other hand, because firms do not internalize consumer surplus, there may also be too few products. These two effects, which work in opposite directions, are highlighted in Spence (1976) and Mankiw and Whinston (1986) in the context of a single-product oligopoly. In a multi-product oligopoly, however, there exists another factor influencing the equilibrium product offerings: firms' incentives to avoid cannibalization of their own products, which may drive the equilibrium towards too few products. Overall, because of these 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 may need to be more lenient. Conversely, if a merger reduces product offerings when there are already too few products in the market, then merger policies may need to be stricter.

Product variety is an important determinant of welfare, and firms' product portfolio may be an important margin of adjustment after a merger. Section 6.4 of the 2010 Horizontal Merger Guidelines, for example, states that antitrust agencies consider the welfare effects of mergers through the adjustment of product variety: "Mergers can lead to the efficient consolidation of products ... In other cases, a merger may increase variety ... If the merged firm would withdraw a product that a significant number of customers strongly prefer to those products that would remain available, this can constitute a harm to customers over and above any effects on the price or quality of any given product. If there is evidence of such an effect, the Agencies may inquire whether the reduction in variety is largely due to a loss of competitive incentives attributable to the merger."

We study our research questions in the context of the U.S. smartphone market. 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)). Moreover, 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, we develop a structural model of consumer demand and firms' product and pricing decisions, and estimate the model using data 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. (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 supply. The estimation results are intuitive: on average and ceteris paribus, 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 corresponding estimated demand coefficients. We then use our quality index to propose a measure of product variety such that adding a product identical to an existing product 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. We also obtain bounds on fixed costs. Specifically, we assume that the observed product portfolio of a smartphone 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. 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. 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 its lower bound, total surplus increases. To put this ratio in perspective, note that the average of all estimated upper bounds is about 1.2 times the average lower bound. 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 in March 2013. We also repeat the simulation for a Samsung-Motorola merger and an LG-Motorola merger. 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 36 potential products, implying a choice set of 2^{36} ($\approx 6.9 \times 10^{10}$) 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.[1]

Using this algorithm, we find that after the Samsung-LG merger, the number of products in the market decreases. On average, the merged firm drops three 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 as well (Samsung-Motorola and LG-Motorola).

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 to an extensive list of variations to the demand side of the model (4 such robustness analyses), to the supply side (5 such robustness analyses) and to the merger simulation specifications (7 such robustness analyses).

By studying the welfare implications of product proliferation and how competition affects them, this paper contributes to the literature of endogenous product choice. Examples in this literature include Draganska, Mazzeo and Seim (2009), Fan (2013), Sweeting (2013), Eizenberg (2014), Nosko (2014), Berry, Eizenberg and Waldfogel (2016) and Wollmann (2017).[2] In terms of methodology, the paper is closely related to Eizenberg (2014), which also studies multi-product firms' discrete product choice for a different research question. Thus, both papers face the challenge of computing an equilibrium where firms have a large discrete choice set in the counterfactual simulations. We tackle the problem using different approaches though. Eizenberg (2014) directly restricts the firms'

[1] In 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 0.6% even as we increase the number of potential products to 10.

[2] Other examples include Seim (2006), Watson (2009), Chu (2010), Crawford and Yurukoglu (2012), Crawford, Shcherbakov and Shum (2015), Orhun, Venkataraman and Chintagunta (2015) and Hristakeva (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).

choice set to the extent that there are only 512 possible equilibrium configurations. This approach is reasonable in his setting because Eizenberg (2014) studies the effect of removing a product. It is therefore plausible to assume that products that are not close substitutes do not adjust. Our paper focuses on mergers. It is unclear, ex ante, which products are unlikely to be adjusted. We thus take a different approach as explained before. In terms of topics, this paper is closely related to Fan (2013), which 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. Interestingly, despite the differences in focus and industries, the two papers make similar policy recommendations: merger policies may need to 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. By contrast, Wollmann (2017) finds that product adjustments mitigate the negative merger effect in the commercial truck industry, while we find that they exacerbate it in the smartphone industry. Note that both papers find product exits by the merging parties and product entries by non-merging firms. The difference is about the net change in product offerings. One potential explanation for the difference is that the commercial truck industry is segmented by gross vehicle weight rating.[3] In such a market, the merged firm would hold near monopoly power in some segments and earn high markups if there were no product adjustments. Other firms thus have strong incentives to enter these segments, which alleviates the harm of the merger. The smartphone market, on the other hand, is much less segmented. Here, a merger does not dramatically increase concentration (and thus does not generate strong entry incentives) in any "segment". As a result, the incentive to avoid cannibalization dominates, and the merged firm drops more products than what other firms add. Therefore, due to these differences in market structure, Wollmann (2017) is more about the potential entry defense used in antitrust and this paper is more about an antitrust authority's concern regarding the (potentially negative) merger effect on product variety.

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 (2016) examines the operation system network effect. Finally, Yang (2017) 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.

[3] According to Wollmann (2017), "GWR [gross vehicle weight rating] determines the possible uses of a vehicle. Since carrying loads in excess of it is illegal and unsafe, and since it increases price, buyers purchase vehicles with the minimum GWR that safely covers their needs."

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.

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.[4] 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 serve only one regional market and often provide only prepaid service plans, we drop these observations from our analyses.[5] 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 length 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 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 units. 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

[4]The 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.

[5]The 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 (hour)	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		

[a]Four observations in our sample have a 0 price.

[b]One product in our sample (BlackBerry 8830) does not have a camera.

average of 10 products in a given month.

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

[a]Averaged across months.

To see whether the multiple products offered by a smartphone firm are similar or different in quality and price, in Table 3, 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/month combination. 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 the 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 (hour)	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

We use a random-coefficient discrete choice model to describe smartphone demand. Since our data are aggregated to 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:

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

where q_j is a quality index which depends on the observable product characteristics $\boldsymbol{x}_j$ as $q_j = \boldsymbol{x}_j\boldsymbol{\theta}$, where $\boldsymbol{\theta}$ are parameters to be estimated.[6] 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 element 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 fees of carrier c's network service in period t as well as a general time trend in consumers' tastes

[6] In other words, we assume that the consumer utility depends on the product characteristics only through the quality index. This parsimonious functional form allows us to estimate the heterogeneous preferences for all important phone characteristics even if some of the characteristics' own random coefficient variances cannot be estimated precisely, due to lack of variation, if we allow each characteristic to have an independent random coefficient. In Appendix B, we conduct a robustness analysis where we use the baseline estimates but assume that the coefficients are independent across characteristics. We find our results are robust.

for smartphones, we include a carrier/year fixed effect.[7] 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 share of choice j in period t as:

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

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

We define the mean utility of j in period t as

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

and invert it out based on equation (2) following Berry, Levinsohn and Pakes (1995).

3.2 Supply

We use a static three-stage game to describe the supply side of the model. In the first stage, smartphone firms choose their products. In the second stage, they 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 Decision on Prices

In the final stage of our model, carriers choose retail prices after observing the set of products available on each carrier (denoted by $\mathcal{J}_{ct}$), wholesale prices (w_{jt}) and demand shocks (ξ_{jt}). 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

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

[7] By 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.

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

$$\tilde{w}_{jt} = p_{jt} + [\Delta_{ct}^{-1} \boldsymbol{s}_{ct}]_{jt}, \tag{5}$$

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 $\boldsymbol{s}_{ct} = (s_{jt}, j \in \mathcal{J}_{ct})$. We denote the equilibrium of this stage by $p_{jt}^{*}(\tilde{\boldsymbol{w}}_t, \boldsymbol{q}_t, \boldsymbol{\xi}_t)$, where $\tilde{\boldsymbol{w}}_t = (\tilde{\boldsymbol{w}}_{jt}, j \in \mathcal{J}_t)$ and $(\boldsymbol{q}_t, \boldsymbol{\xi}_t)$ 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), carrier/year fixed effects (γ_{ct}), and a jt-specific shock (η_{jt}).[8] Specifically, we assume that the marginal cost is $mc_{jt} = \gamma_{c(j)t} + \gamma_1 exp(q_j) + \eta_{jt}$.[9] If we let $\tilde{mc}_{jt} = mc_{jt} - b_{c(j)t}$ and $\tilde{\gamma}_{c(j)t} = \gamma_{c(j)t} - b_{c(j)t}$, we have:

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

Note that $\tilde{w}_{jt} - \tilde{mc}_{jt} = w_{jt} - mc_{jt}$. A smartphone firm m's profit-maximizing problem is therefore

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

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

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

or equivalently,

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

where $\boldsymbol{s}_{mt} = (s_{jt}, j \in \mathcal{J}_{mt})$, 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

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

which we bring to 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 such as a non-linear pricing model or a joint price setting model for robustness analyses.

[8] We allow marginal cost to vary across carriers because different radio technologies are used for products sold by different carriers. Moreover, carriers sometimes require smartphone firms to preload specific software on a smartphone, contributing to cost differences.

[9] Following the literature, we assume that marginal cost is convex in quality (we expect γ_1 to be positive) so that the profit function is concave in quality.

3.2.2 Decision on Products

In the first-stage of the model, smartphone firms choose products. In other words, we assume that the upstream firm makes the product decision, in contrast to Eizenberg (2014). Note that in the PC market studied in Eizenberg (2014), the upstream firms (i.e., the CPU manufacturers) produce only a component of the final product. Therefore, it seems natural to assume that the downstream firms make a product decision in the PC market. In our setting, however, the upstream firms make the final products directly, and it seems more natural to assume that they make the product decisions. Nash equilibrium implies that given competitors' product portfolios at the equilibrium, any deviation from a smartphone 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. Note that while the majority of the products in our study are sold through only one carrier, 12% are sold through multiple 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, smartphone firm m's expected profit should not increase if product $\tilde{j}$ in its portfolio is removed, i.e.,

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

where $\pi_{mt}\left(\boldsymbol{q}_t,\boldsymbol{\xi}_t,\boldsymbol{\eta}_t\right)$ is the equilibrium variable profit for firm m (at the stage-2 and stage-3 pricing equilibrium), $F_{\tilde{j}t}$ is the fixed cost, $\pi_{mt}\left(\boldsymbol{q}_t\backslash q_{\tilde{j}},\boldsymbol{\xi}_t\backslash\xi_{\tilde{j}t},\boldsymbol{\eta}_t\backslash\eta_{\tilde{j}t}\right)$ 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.[10] 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

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

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

[10] If product $\tilde{j}$ is 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 smartphone 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.

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. This estimation strategy relies on the timing assumption that the demand and marginal cost shocks are realized after the product choice.[11] 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.[12] 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. The market size used in the estimation is 30 million, about 10% of the U.S. population during the sample period. Our results are robust to other market size measures.

As for the fixed cost, we use inequalities (11) and (12) to obtain the bounds. 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., $E_{(\boldsymbol{\xi}_t,\boldsymbol{\eta}_t)}\pi_{mt}\left(\boldsymbol{q}_t,\boldsymbol{\xi}_t,\boldsymbol{\eta}_t\right)-E_{(\boldsymbol{\xi}_t\backslash\xi_{\tilde{j}t},\boldsymbol{\eta}_t\backslash\eta_{\tilde{j}t})}\pi_{mt}\left(\boldsymbol{q}_t\backslash q_{\tilde{j}},\boldsymbol{\xi}_t\backslash\xi_{\tilde{j}t},\boldsymbol{\eta}_t\backslash\eta_{\tilde{j}t}\right)$. The expectation is taken over the demand and marginal cost shocks $(\boldsymbol{\xi}_t,\boldsymbol{\eta}_t)$. We assume that the demand and marginal cost shocks each follow 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.[13] 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 $\tilde{j}\notin\tilde{\mathcal{J}}_t$. Similar to Berry, Eizenberg and Waldfogel (2016), we use these product/time-specific bounds directly in our welfare analyses instead of (set) estimating a parametric function of the fixed cost. We do so to avoid making assumptions about the parametric functional form of the fixed cost and about its error terms (e.g., whether the error terms are structural errors or measurement errors, and an independence assumption about the error terms).

[11] Similar timing assumption is made in, for example, Eizenberg (2014) and Wollmann (2017).

[12] In Supplemental Appendix SA, we plot the estimated demand shocks $\hat{\xi}_{jt}$ for three groups of observations separately: (1) jt s.t. j is newly added to the market in period t; (2) jt s.t. j is discontinued after period t; and (3) all other jt. We find that the distributions of demand shocks do not seem to be very different across these three groups. This is also true for marginal cost shocks. While not a proof, these plots are assuring because the distributions could be quite different even under our exogeneity assumption.

[13] Our results are robust when we draw these shocks from their empirical distribution instead.

However, there is a disadvantage of this approach: we implicitly assume that the total fixed cost of a firm is the sum of the fixed cost for each product, which means we do not allow economies or diseconomies of scope in fixed costs. To address this concern, we conduct a robustness analysis in Supplemental Appendix SB where we assume a parametric function of the fixed cost and estimate the degree of economies or diseconomies of scope in fixed costs following the moment inequality literature.[14]

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

Table 4: Estimation Results

	Parameter	Std. Error
Demand		
Quality coefficient		
battery talk time (hour)	0.056***	0.013
camera resolution (megapixel)	0.093***	0.036
chipset generation 2	0.460***	0.113
chipset generation 3	0.718***	0.147
chipset generation 4	1.055***	0.200
chipset generation 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.

find that a one-hour increase in battery talk time is equivalent to a price decrease of 6.5 dollars for

[14]See, for example, Chernozhukov, Hong and Tamer (2007), Holmes (2011), Pakes, Porter, Ho and Ishii (2015) and Wollmann (2017).

an average consumer. Similarly, a one-megapixel increase in camera resolution is equivalent to a 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.[15] 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.[16]

Table 5 reports the price semi-elasticities for the 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 table shows that a \$10 increase in the price of a product leads to about 6% decrease in its demand.[17] 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 March 2013. (Row i, Column j): percentage change in market share of product j with a \$10 change in product i's retail price.

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

[15] Note 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.

[16] See Appendix A for a list of 39 flagship products in our data.

[17] We do not compute price elasticity because we have data on only the subsidized retail price, and a one percent change in the subsidized retail price is not a one percent change in the true cost for consumers. As mentioned, the true cost for a consumer to buy a smartphone is the sum of the subsidized price and the price of a service plan.

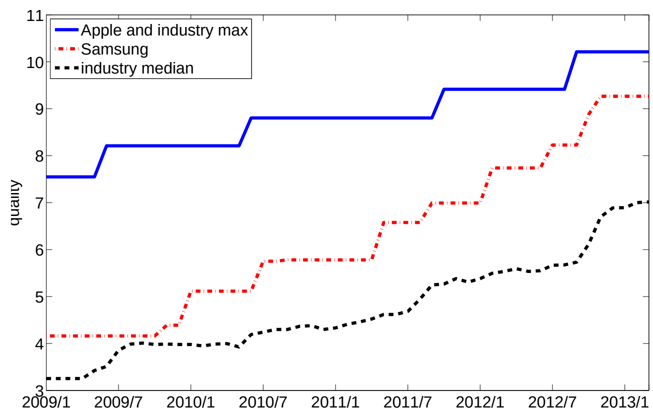
Table 6: Demand Elasticities with Respect to Quality

	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 March 2013. (Row i, Column j): percentage change in market share of product j with a 1 percent change in product i's quality.

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.

Figure 1: Smartphone Quality over Time

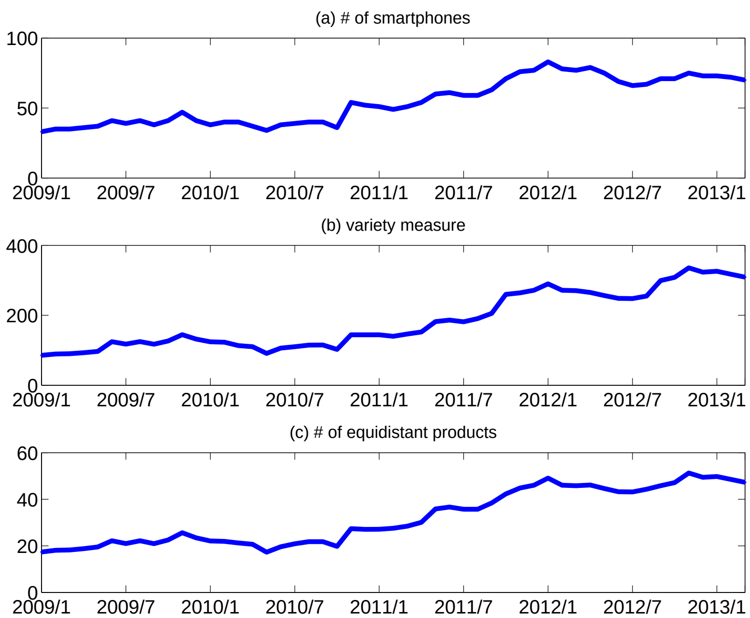


The number of smartphones also increases over time. However, such an increase does not necessarily lead to an increase in product variety. For example, if firms use a strategy of obfuscation, i.e., they add products that differ from existing products only in trivial features such as names or colors, this does not really contribute to product variety. To show the evolution of product variety over time, we use the same quality index used in Figure 1 to construct a measure of product variety. Specifically, we measure product variety in a market with n products as $\left[\sum_{k=2}^{n}\left(q^{(k)}-q^{(k-1)}\right)^{1/2}\right]^2$, where $q^{(1)} < \cdots < q^{(n)}$ 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., $q^{(n)} - q^{(1)}$) and the number of products n, this measure is maximized when products are equidistant. The maximum is $(n-1)\left(q^{(n)} - q^{(1)}\right)$. Second, this maximum is increasing in the number of products n and the quality range $\left(q^{(n)} - q^{(1)}\right)$. 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.

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.

Figure 2: Product Variety over Time

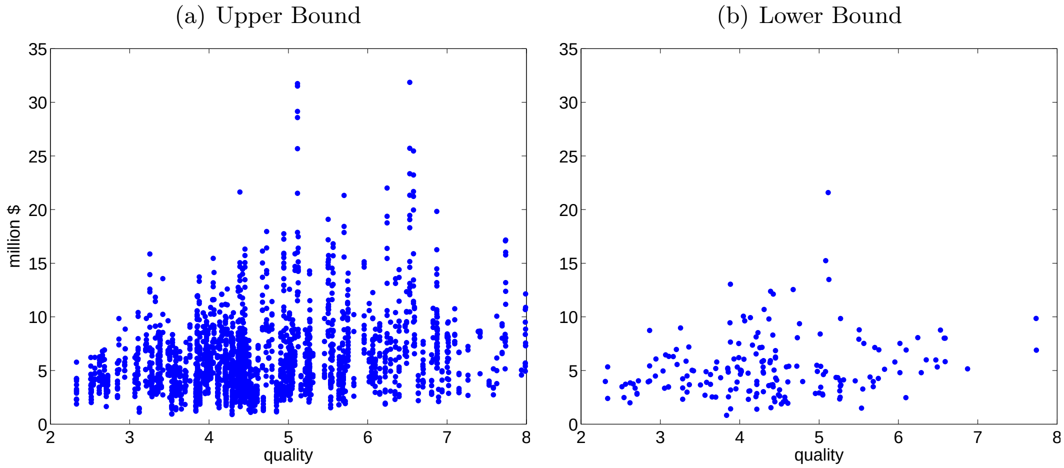


On the supply side, we find that marginal cost increases in product quality. Based on the estimates of the demand and marginal cost functions, we obtain the fixed cost bounds. As mentioned, we can obtain an upper bound for each product in the data and a lower bound for any product not in the data. Figure 3 plots the upper bound of the fixed cost for non-flagship smartphone/month combinations in the data (in Figure 3(a)) and the lower bound for discontinued non-flagship products (in Figure 3(b)). The horizontal axis represents the quality of a product, the same quality index in Figure 1. The vertical axis represents the bound of the fixed cost. Figure 3 suggests that the bound of the fixed cost is positively correlated with product quality. The average upper bound in Figure 3(a) is 6.16 million dollars; and the average lower bound in Figure 3(b) is 5.27 million dollars.

5 Counterfactual Simulations

In this section, we conduct counterfactual simulations to address the two research questions of interest. As mentioned, there are 39 flagship smartphones in our data. Flagship products are

Figure 3: Bounds of Fixed Costs (Million $)



usually equipped with cutting-edge technologies and thus require a sizable sunk innovation cost. Our static model of product choice, which focuses on product variety instead of product innovation, thus is most suitable to describe firms' decision on non-flagship products given the quality frontier. Therefore, in this section, we focus on non-flagship products in our baseline and show the robustness of our results as we add flagship products into consideration.

5.1 Are there too few or too many products?

To address this question, we first conduct counterfactual simulations where we remove a product.[18] 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 for each simulation draw of the demand and marginal cost shocks, compute the corresponding consumer surplus and producer surplus, and then take the average across all draws. We repeat this counterfactual simulation removing the median (highest)-quality non-flagship 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 is removed: consumer surplus decreases by 0.92, 2.52 and 12.67 million dollars in the lowest-, median- and highest-quality scenarios, respectively. Note that the revenues generated by these products in March 2013 are, respectively, 8.19, 32.26 and 66.39 million dollars, about 6 to 15

[18] As mentioned in Footnote 10, for any product removed, we remove it from all carriers. Our finding is robust to removing a smartphone/carrier combination instead.

Table 7: Welfare Changes When a Product Is Removed, March 2013 (Million \$)

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

times the consumer surplus changes from removing the corresponding product.[19] Such decreases in consumer welfare are partially due to changes in prices after a product is a 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 accounts for most of the total change in consumer surplus.

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 remove a product, we also remove the logit error term corresponding to this product, which is independent of other logit error terms. To address this concern, we recalculate Δ(consumer surplus) without accounting for changes in the set of logit error terms (see Supplemental Appendix SC for details). The changes in consumer surplus without changes in logit error terms are indeed smaller: they become -0.46, -1.51, and -10.35 million dollars. However, the sum of the four rows is still negative.

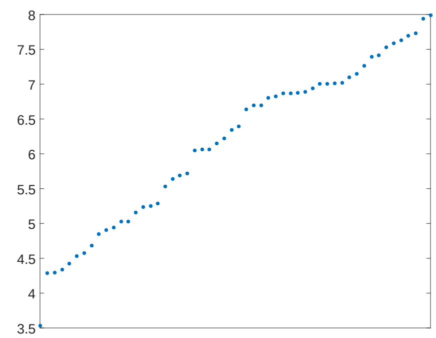
Comparing results across the three columns, we can see that the changes in all welfare measures become larger as we move from removing the lowest to the highest-quality product. The main conclusion, however, remains the same: total welfare decreases even considering the maximum possible saving in the fixed cost. In fact, when we repeat the above exercise for each of the 70 products (including both the flagship and the non-flagship products) in March 2013, we find that our results hold in all 70 simulations. Specifically, Δ(consumer surplus), Δ(carrier surplus) and Δ(smartphone producer variable profits) are always negative; the sum of them plus the upper bound of the removed product's fixed cost is still always negative. These results indicate that removing any product in the market leads to a decrease in total welfare, even considering 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

[19]To compute the total revenue, we consider an average service plan price of 60 dollars per months over 24 months. The revenue generated by product j in month t is $(60 \times 24 + p_{jt})q_{jt}$ dollars.

removing any two products and find that the same conclusion 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 non-flagship 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

Figure 4: Quality of Products in March 2013



the product portfolio of Samsung, LG, HTC or Motorola, 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 for the added product. 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
Δ(consumer surplus)	2.43	2.43	2.51	2.79
Δ(carrier surplus)	1.26	1.27	1.29	1.53
Δ(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 change in total welfare is the sum of the first three rows minus the fixed cost of the added product. We find that the former is about 2.3 times the lower bound of the latter 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 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 Δ(consumer surplus) in Row 1 by that without accounting for changes in logit error terms, the ratio of the sum of the first three rows to the lower bound of the fixed cost varies 1.6 and 2 (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.[20] The literature (e.g. Spence (1976) and Mankiw and Whinston (1986)) has identified two countervailing forces determining the efficiency of the equilibrium product offerings in an oligopolistic competition: 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. Compared to single-product firms studied in these papers, the multi-product firms in our paper have an additional reason to restrict product offerings: to avoid cannibalization. In fact, we find that all smartphone firms in March 2013 are likely to offer more products if they ignore cannibalization. Specifically, we repeat the counterfactual simulation in Table 8 for all smartphone firms in March 2013. To study firm behavior without the cannibalization consideration, we now focus on "product variable profit" (π_{jt}) instead of "firm variable profit" ($\pi_{mt} = \sum_{j \in \mathcal{J}_{mt}} \pi_{jt}$). If a firm ignores cannibalization, it would want to add the product if $\pi_{jt} > F_{jt}$. We find that, across all smartphone firms, the ratio of the added product's variable profit to the lower bound of its fixed cost varies from 2.08 to 2.21, implying that as long as the fixed cost is not more than 2.08 times of its lower bound, all smartphone firms in March 2013 would want to deviate from their current product portfolios by adding the product studied in Table 8. This result suggests that firms' cannibalization concerns indeed motivate firms to restrict product offerings, which partially contributes to our finding that there are too few products in the market.[21]

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,[22] 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

[20] Another (and the ideal) way to address this question is to simulate what the social planner would have chosen. This is the approach taken by Berry, Eizenberg and Waldfogel (2016). However, our problem is "larger": there are 70 products, implying that the social planner's decision is a vector of more than 70 binaries, i.e., a choice set of larger than $2^{70} \approx 1.8e^{21}$ for the social planner (It is larger than 2^{70} because we should also allow the social planner to add some products which are not part of the existing 70 products.) When we adapt the heuristic algorithm explained later in Section 5.2 (and combine it with certain assumptions on the fixed cost) to solve the social planner's problem, we indeed find that the social planner would add products without dropping any product.

[21] In a related paper, Berry, Eizenberg and Waldfogel (2016) find too much product variety in the local radio market. Our study differs from their work by considering product variety in a multi-product oligopoly setting instead of a single-product oligopoly setting. As explained here, this difference in market structure may explain the difference in results: compared to a single-product firm, a multi-product firm has an additional reason for not adding a product, i.e., to avoid cannibalization.

[22] We also repeat the merger simulation for September 2012 and March 2012, and obtain qualitatively similar results. In the interest of space, we do not report the results in the paper.

the new pricing equilibrium for given product offerings in the market.

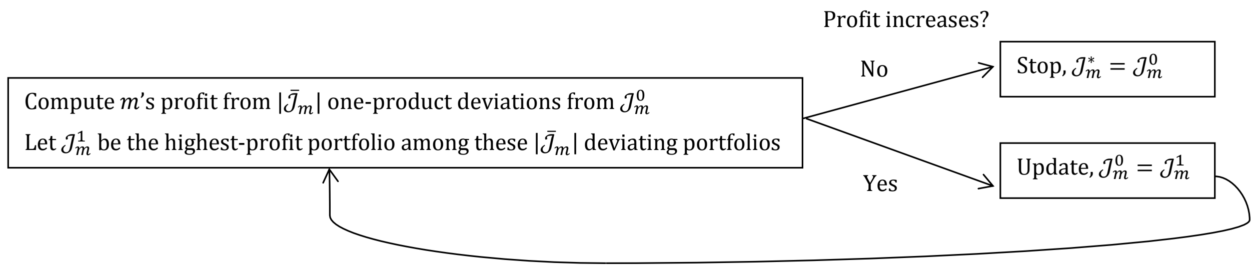
Computing the post-merger product-choice equilibrium can be challenging because a firm can choose to drop any set of products or add any number of products after a merger, leading to a potentially very large action space for product choice. To keep the problem tractable, we restrict the set of potential 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.[23] 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 at either or both of these qualities. 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.

Even with this restricted set of potential products, the action space for a firm can still be too large 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, in the baseline when we only consider non-flagship products, 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, $\bar{\mathcal{J}}_m = \{j_1, ..., j_n\}$). We start with a portfolio $\mathcal{J}_m^0 \subseteq \bar{\mathcal{J}}_m$ (for example, $\mathcal{J}_m^0 = \{j_1, ..., j_{n_1}\}$ where $n_1 \leq n$). We compute firm m's profit from each of the following deviations from $\mathcal{J}_m^0$: $\mathcal{J}_m^0 \backslash \{j_k\}, k = 1, ..., n_1$ or $\mathcal{J}_m^0 \cup \{j_k\}, k = n_1 + 1, ..., n$. 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

[23]Since 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 B, 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



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 whose action space grows exponentially in the number of potential products (choosing from $2^{|\bar{\mathcal{J}}_m|}$ product portfolios) into one whose action space grows linearly (in each step, evaluating $|\bar{\mathcal{J}}_m|$ portfolios).[24]

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. 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 if 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 in Supplemental Appendix SD. 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. In addition, given that we impose a one-product deviation restriction in each step, we also check and confirm that, at the equilibrium found by the heuristic algorithm in our merger simulations below, no firm has a two-product profitable deviation.

We embed this algorithm in a best-response iteration, where we start with the pre-merger equilibrium and let 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 over 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. Following the learning algorithm

[24] Jeziorski (2014) uses a similar idea to avoid an 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. Jia (2008) also faces a similar large action space problem in studying chain store location choice. She solves the issue by exploiting lattice theory, transforming the profit-maximizing problem into a search for fixed points defined by the necessary optimality conditions. A critical assumption for her approach to work is that the profit of one store increases when the chain opens another store, i.e., stores of the same chain are complementary. Such a complementarity assumption is unlikely to hold in our context of product choice.

in Lee and Pakes (2009) where firms update their best-response portfolio simultaneously in each round of the best-response iteration, we also obtain the same equilibrium.[25]

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 fixed-cost draws. Specifically, for each product in the data, we have obtained an upper bound of its fixed cost (denoted by $\bar{F}_{\tilde{j}t}$). For such a product, we uniformly draw five fixed-cost values from the range $\left[0.5\bar{F}_{\tilde{j}t}, \bar{F}_{\tilde{j}t}\right]$. Similarly, for each potential product not in the data, we have obtained a lower bound of its fixed cost $\underline{F}_{\tilde{j}t}$. We draw five fixed-cost values from $\left[\underline{F}_{\tilde{j}t}, 5\underline{F}_{\tilde{j}t}\right]$. In Appendix B, 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 2.80 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 0.60. 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 0.8, 1, 1, and 0, respectively. Overall, the product variety measure decreases by 23.33 (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 measure (336.91) is "as if" there are 51.44 equidistant products. Therefore, a change of -23.33 in the product variety measure is equivalent to a decrease of about 3.49 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 1.75 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 9.22 dollars. Overall, sales for the merged firm decrease and those for the non-merging firms increase, with a net change of -89,558 units. The decrease in product offerings and the increase in prices eventually lead to a reduction in consumer surplus of around 28.60 million dollars. Carriers are also worse off. The total smartphone profit, however, increases by around 12.93 million dollars, among them, 1.69 million dollars are attributed to the increase in the merged firm's profit and the remaining 11.24 million dollars are due to changes in non-merging

[25] That said, we cannot rule out the possibility of multiple equilibria. In a similar context, Lee and Pakes (2009) and Wollmann (2017) argue that one could consider a sequence of movements in the best-response iteration as part of the model structure.

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

	Variable	Pre-merger	Post-merger	Change
(1)	Number of products	70	67.20	-2.80
(2)	merged firm	30	26.60	-3.40
(3)	non-merging firms	40	40.60	0.60
(4)	Variety	360.25	336.91	-23.33
(5)	Sales-weighted avg quality	8.40	8.42	0.02
(6)	merged firm	7.32	7.34	0.02
(7)	non-merging firms	6.247	6.248	0.001
(8)	Sales-weighted avg price ($)	110.00	111.75	1.75
(9)	merged firm	156.08	165.30	9.22
(10)	non-merging firms	91.23	91.73	0.50
(11)	Total sales	7,002,268	6,912,710	-89,558
(12)	merged firm	2,027,077	1,881,110	-145,967
(13)	non-merging firms	4,975,192	5,031,600	56,408
(14)	Consumer surplus (million $)	1681.21	1652.62	-28.60
(15)	Carrier profit (million $)	1266.42	1250.60	-15.82
(16)	Smartphone firm profit (million $)	1116.96	1129.89	12.93
(17)	merged firm	273.71	275.40	1.69
(18)	non-merging firms	843.25	854.49	11.24

firms' profits with an average increase of 1.02 million dollars per non-merging firm. In sum, overall welfare decreases by around 31.49 million dollars.

Altogether, 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 in this market may need to be stricter when we take into account the effect of a merger on product offerings.

This conclusion is consistent with a comparison of our merger simulation with one where we keep the set of products fixed and allow firms to adjust only prices after the merger. In the latter 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 -28.60, -15.82 and 12.93 million dollars when post-merger adjustments in both product offerings and prices are allowed. The decrease in total surplus is also smaller (-21.31 vs. -31.49), again suggesting that product adjustments exacerbate the negative merger effect.

As mentioned, in the above baseline simulation, we consider only non-flagship products. In Appendix B, we show that as we add more products into consideration (e.g., when we allow firms to also adjust old flagship products, or even all flagship products), our simulation results are robust.

6 Robustness Analyses

We have conducted robustness checks that examine 16 variations to the demand specification, the pricing model, the definition of potential products, the post-merger brand effect, the range of fixed costs and identities of merging firms. We present three such analyses in this section (and the other 13 robustness analyses in Appendices B and SB). In this section, 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 first re-estimate the model and then 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. One way we address this concern is that we report Δ(consumer surplus) ignoring changes in logit errors (see Section 5). In this section, we address this concern by conducting two robustness analyses where we add more random coefficients in order to allow for a 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 four random coefficients, one for each carrier dummy variable. 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 (compared to their corresponding means) and statistically insignificant. The estimates for the parameters common to the two models are robust. Moreover, all qualitative conclusions we draw from counterfactual simulation results also hold (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

Table 10: Robustness Analysis: Allowing an Apple Random Coefficient

(a) Estimation Results

	Parameter	Std. Error
Demand		
Quality coefficient		
battery talk time (hour)	0.052***	0.016
camera resolution (megapixel)	0.109***	0.046
chipset generation 2	0.444***	0.137
chipset generation 3	0.743***	0.180
chipset generation 4	1.145***	0.261
chipset generation 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 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)	-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)	2.73	2.74	2.79	3.25
Δ(carrier surplus)	1.75	1.77	1.79	2.15
Δ(smartphone producer variable profits)	1.22	1.21	1.20	1.88
Lower bound of added fixed costs	2.39	2.40	2.41	3.04

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

Variable	Pre-merger	Post-merger	Change
Number of products	70	63.60	-6.40
Variety	324.84	287.37	-37.47
Sales-weighted avg quality	6.879	6.877	-0.003
Sales-weighted avg price ($)	94.62	98.93	4.31
Total sales	7,398,499	7,210,223	-188,277
Consumer surplus (million $)	2632.83	2567.94	-64.90
Carrier profit (million $)	1648.47	1610.09	-38.39
Smartphone firm profit (million $)	1778.79	1811.00	32.22

Table 11: Robustness Analysis: Allowing Carrier Random Coefficients

(a) Estimation Results

	Parameter	Std. Error
Demand		
Quality coefficient		
battery talk time (hour)	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 products	70	44.40	-25.60
Variety	379.09	233.56	-145.52
Sales-weighted avg quality	8.38	8.44	0.05
Sales-weighted avg price ($)	94.71	102.48	7.77
Total sales	7,893,047	7,692,413	-200,634
Consumer surplus (million $)	2230.96	2170.90	-60.06
Carrier profit (million $)	1577.60	1558.58	-19.01
Smartphone firm profit (million $)	1301.04	1374.70	73.66

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 iPhone prices jointly to maximize their joint profit from iPhones.[26] 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.

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 products	70	67.40	-2.60
Variety	360.25	338.59	-21.66
Sales-weighted avg quality	8.34	8.36	0.02
Sales-weighted avg price ($)	128.08	130.38	2.29
Total sales	6,792,576	6,696,152	-96,424
Consumer surplus (million $)	1632.88	1602.07	-30.81
Carrier profit (million $)	1225.29	1208.05	-17.24
Smartphone firm profit (million $)	1044.85	1058.31	13.46

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

[26]At 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.

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 the welfare effect of a merger may be worse when we take into account the effect of a merger on product choice.

We conclude by highlighting a few caveats of the paper. First, our model is static. We have two pricing stages and a large action space for product choice. Therefore, estimating a dynamic model in our setting is intractable or would require us to give up some richness in describing the set of products available in the market and the set of potential products. As a result, similar to many papers in the endogenous product choice literature, our paper uses a static model to describe consumer demand and firm behavior.[27] On the supply side, this modeling choice is somewhat justifiable as we focus on non-flagship products in the baseline and such products presumably do not involve a large sunk cost such as the R&D cost (and we conduct robustness analyses by including flagship products). However, consumers may be dynamic, which will lead to firm dynamic behavior. For 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.[28] 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.

Second, our model does not explain the choice of carriers for each product by a smartphone firm. We could expand our definition of potential products for each firm to allow the firm to choose carriers. For example, we could define potential products for a firm as follows: (product j, AT&T), (j, T-Mobile), ..., (j, AT&T and T-Mobile), $\ldots$ However, given that doing so increases the computational burden substantially and that in the data, we do not observe smartphone firms moving products from one carrier to another, we leave this for future research.

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[27] See, for example, Seim (2006), Fan (2013), Eizenberg (2014), Crawford, Shcherbakov and Shum (2015) and Berry, Eizenberg and Waldfogel (2016).

[28] For 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.

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Appendices

A List of Flagship Smartphones

Our list of flagship products is mainly based on a list supplied by our data vendor. We corroborate and supplement the list with products prominently featured in Consumer Electronics Shows and products hailed as flagship products for a given firm in the US and international markets in a large number of news articles. Note that this definition is at the product level and does not change over time. One could argue that when a new flagship product of a smartphone firm is introduced, its old flagship products are no longer flagship products. In Appendix B, we repeat our merger simulation considering the old flagship products to be non-flagship products. We also show in Appendix B that our results are robust when we include all products (non-flagship and flagship products), implying that our results are not sensitive to the definition of flagship products.

Flagship Products (2009/01 – 2013/03)

Brand	Model
HTC	G1
	myTouch 3G
	Hero
	myTouch 4G
	Desire HD
	Evo 3D
	Sensation
	One X
	Droid DNA
	Windows Phone 8X
LG	Optimus One
	Optimus 2X
	Optimus G
Motorola	Droid
	Droid X
	Atrix 4G
	Droid Bionic
	Droid Razr
	Droid Razr Maxx
	Droid Razr M

Brand	Model
Apple	iPhone 3G
	iPhone 3G
	iPhone 4
	iPhone 4s
	iPhone 5
BlackBerry	88XX
	Curve
	Storm
	Bold
	Tour
	Torch
	Bold Touch
	BlackBerry 10
Nokia	Lumia 900
	Lumia 920
Samsung	Galaxy S
	Galaxy S II
	Galaxy S III
	Galaxy Note II

B Additional Merger Simulations

In this section, we first show that our Samsung-LG merger results are robust to several variations to the setup of the merger simulation (Section B.1). We then report the results of two alternative mergers that involve smaller firms, and show that while the magnitude of the merger effects unsurprisingly becomes smaller, our qualitative conclusion still holds (Section B.2).

B.1 Merger Simulations with Different Specifications

We repeat the Samsung-LG merger simulation with four variations in this section. 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. In the third variation, we allow firms to adjust flagship products as well as non-flagship products. In the fourth variation, we treat the coefficient of each product characteristic as an independent random coefficient.

B.1.1 Variation 1. Post-merger Brand Effect

As mentioned in Footnote 23, 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 B.1 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 B.1: Samsung-LG Simulation Results Using the Average Brand Effect for the Merged Firm

	Variable	Pre-merger	Post-merger	Change
(1)	Number of products	70	64.80	-5.20
(2)	merged firm	30	23.80	-6.20
(3)	non-merging firms	40	41.00	1.00
(4)	Variety	360.25	342.34	-17.90
(5)	Sales-weighted avg quality	8.40	8.46	0.06
(6)	merged firm	7.32	7.48	0.16
(7)	non-merging firms	6.247	6.248	0.001
(8)	Sales-weighted avg price ($)	110.00	114.76	4.76
(9)	merged firm	156.08	180.81	24.74
(10)	non-merging firms	91.23	91.70	0.47
(11)	Total sales	7,002,268	6,843,533	-158,736
(12)	merged firm	2,027,077	1,770,898	-256,178
(13)	non-merging firms	4,975,192	5,072,634	97,443
(14)	Consumer surplus (million $)	1681.21	1634.62	-46.60
(15)	Carrier profit (million $)	1266.42	1235.62	-30.80
(16)	Smartphone firm profit (million $)	1116.96	1134.38	17.42
(17)	merged firm	273.71	271.63	-2.08
(18)	non-merging firms	843.25	862.75	19.49

B.1.2 Variation 2. Fixed Costs

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

(1) $\left[\bar{F}_{jt} - (\bar{F} - \underline{F}), \bar{F}_{jt}\right]$ for a product in the data and $\left[\underline{F}_{jt}, \underline{F}_{jt} + (\bar{F} - \underline{F})\right]$ 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) $\left[\bar{F}_{jt} - (L_u(q_{jt}) - L_l(q_{jt})), \bar{F}_{jt}\right]$ for a product in the data and $\left[\underline{F}_{jt}, \underline{F}_{jt} + (L_u(q_{jt}) - L_l(q_{jt}))\right]$ 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.

In Table B.2, we show that the merger simulation results are robust to these two alternative fixed-cost ranges.

Table B.2: 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 products	70	67.20	-2.80
(2)	merged firm	30	24.00	-6.00
(3)	non-merging firms	40	43.20	3.20
(4)	Variety	360.25	341.39	-18.86
(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	6.242	-0.005
(8)	Sales-weighted avg price ($)	110.00	110.02	0.02
(9)	merged firm	156.08	165.63	9.55
(10)	non-merging firms	91.23	90.51	-0.72
(11)	Total sales	7,002,268	6,896,415	-105,853
(12)	merged firm	2,027,077	1,791,381	-235,695
(13)	non-merging firms	4,975,192	5,105,034	129,842
(14)	Consumer surplus (million $)	1681.21	1646.14	-35.07
(15)	Carrier profit (million $)	1266.42	1247.78	-18.64
(16)	Smartphone firm profit (million $)	1081.42	1097.88	16.46
(17)	merged firm	252.96	255.12	2.15
(18)	non-merging firms	828.46	842.76	14.30
	Alternative Fixed-cost Range (2)			
(1)	Number of products	70	67.40	-2.60
(2)	merged firm	30	24.60	-5.40
(3)	non-merging firms	40	42.80	2.80
(4)	Variety	360.25	342.48	-17.76
(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	6.242	-0.005

(8)	Sales-weighted avg price ($)	110.00	110.40	0.40
(9)	merged firm	156.08	166.30	10.22
(10)	non-merging firms	91.23	90.57	-0.66
(11)	Total sales	7,002,268	6,901,179	-101,089
(12)	merged firm	2,027,077	1,807,624	-219,452
(13)	non-merging firms	4,975,192	5,093,555	118,363
(14)	Consumer surplus (million $)	1681.21	1647.85	-33.37
(15)	Carrier profit (million $)	1266.42	1248.73	-17.69
(16)	Smartphone firm profit (million $)	1084.76	1099.94	15.17
(17)	merged firm	254.73	256.51	1.78
(18)	non-merging firms	830.03	843.43	13.39

B.1.3 Variation 3. Allowing Adjusting Flagship Products

In the baseline merger simulation, we only allow firms to adjust their non-flagship products. We now add more products into consideration. Specifically, we first allow firms to also adjust old flagship products (i.e., flagship products that are no longer at the quality frontier of a smartphone firm) in Column (1) of Table B.3, and then in Column (2), we allow firms to adjust all products. We find that both results are close to the baseline results.

Table B.3: Samsung-LG Simulation Results Allowing Adjusting Flagship Products

	Variable	Change	
		(1) Old Flagship Products Included	(2) All Flagship Products Included
(1)	Number of products	-2.60	-2.60
(2)	merged firm	-3.40	-3.40
(3)	non-merging firms	0.80	0.80
(4)	Variety	-21.31	-24.00
(5)	Sales-weighted avg quality	0.02	0.02
(6)	merged firm	0.02	0.01
(7)	non-merging firms	0.0003	-0.001
(8)	Sales-weighted avg price ($)	1.42	0.82
(9)	merged firm	8.87	7.48
(10)	non-merging firms	0.27	0.22
(11)	Total sales	-87,657	-95,193
(12)	merged firm	-151,913	-171,627
(13)	non-merging firms	64,256	76,434
(14)	Consumer surplus (million $)	-28.16	-31.41
(15)	Carrier profit (million $)	-16.60	-15.45
(16)	Smartphone firm profit (million $)	13.41	13.70
(17)	merged firm	1.75	1.66
(18)	non-merging firms	11.66	12.05

B.1.4 Variation 4. Independent Random Coefficients

In our baseline specification, we assume that the utility of a consumer depends on the product characteristics through a quality index. In other words, the random coefficient for each product characteristic is perfectly correlated. Specifically, the random coefficient for characteristic k is $(\beta + \sigma\mu_i)\theta_k$. In this robustness analysis, we repeat the merger simulation allowing the random coefficient to be independent across k, i.e., to be $(\beta + \sigma\mu_{ki})\theta_k$ where $\mu_{1i}, ..., \mu_{Ki}$ are independent random variables, and β, σ and θ_k are the estimates reported in Section 4. The result in Table B.4 shows that our results are robust to this variation.

Table B.4: Samsung-LG Simulation Results Assuming Independent Random Coefficients

	Variable	Pre-merger	Post-merger	Change
(1)	Number of products	70	66.80	-3.20
(2)	merged firm	30	21.80	-4.20
(3)	non-merging firms	40	29.00	1.00
(4)	Variety	94.83	91.93	-2.91
(5)	Sales-weighted avg quality	5.82	5.85	0.03
(6)	merged firm	5.06	5.09	0.03
(7)	non-merging firms	4.082	4.082	0.001
(8)	Sales-weighted avg price ($)	72.91	76.88	3.97
(9)	merged firm	52.78	61.20	8.43
(10)	non-merging firms	88.15	87.72	-0.43
(11)	Total sales	7,192,967	7,055,617	-137,351
(12)	merged firm	3,099,041	2,883,673	-215,368
(13)	non-merging firms	4,093,927	4,171,944	78,017
(14)	Consumer surplus (million $)	1515.24	1478.08	-37.16
(15)	Carrier profit (million $)	1265.09	1239.79	-25.29
(16)	Smartphone firm profit (million $)	1117.20	1129.91	12.71
(17)	merged firm	514.20	516.93	2.73
(18)	non-merging firms	602.99	612.97	9.98

B.2 Samsung-Motorola Merger and LG-Motorola Merger

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.5. A 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.

Table B.5: Results from Additional Merger Simulations, March 2013

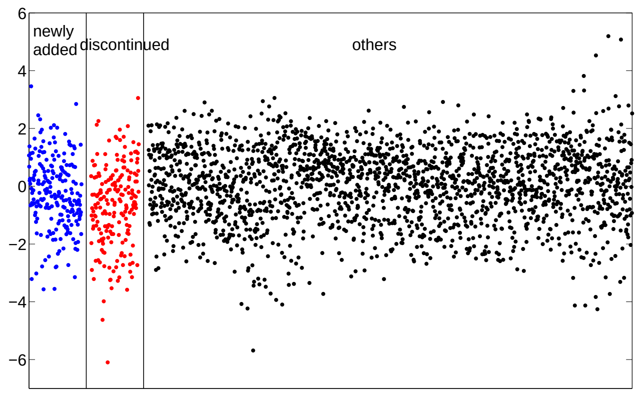
	Variable	Pre-merger	Post-merger	Change
	The Samsung-Motorola Merger			
(1)	Number of products	70	67.80	-2.20
(2)	merged firm	25	22.60	-2.40
(3)	non-merging firms	45	45.20	0.20
(4)	Variety	360.25	350.65	-9.60
(5)	Sales-weighted avg quality	8.401	8.416	0.015
(6)	merged firm	7.359	7.359	0.000
(7)	non-merging firms	6.245	6.246	0.001
(8)	Sales-weighted avg price ($)	110.00	110.36	0.35
(9)	merged firm	161.32	166.03	4.71
(10)	non-merging firms	89.91	90.21	0.29
(11)	Total sales	7,002,268	6,927,079	-75,189
(12)	merged firm	1,970,007	1,840,880	-129,127
(13)	non-merging firms	5,032,261	5,086,199	53,938
(14)	Consumer surplus (million $)	1681.21	1656.47	-24.74
(15)	Carrier profit (million $)	1266.42	1249.10	-17.32
(16)	Smartphone firm profit (million $)	1116.96	1130.92	13.96
(17)	merged firm	275.90	277.88	1.98
(18)	non-merging firms	841.06	853.04	11.97
	The LG-Motorola Merger			
(1)	Number of products	70	69.40	-0.60
(2)	merged firm	19	18.40	-0.60
(3)	non-merging firms	51	51.00	0.00
(4)	Variety	360.25	357.14	-3.10
(5)	Sales-weighted avg quality	8.401	8.407	0.005
(6)	merged firm	7.106	7.090	-0.016
(7)	non-merging firms	6.495	6.496	0.0004
(8)	Sales-weighted avg price ($)	110.00	110.12	0.12
(9)	merged firm	144.92	146.75	1.82
(10)	non-merging firms	105.99	106.14	0.14
(11)	Total sales	7,002,268	6,980,382	-21,886
(12)	merged firm	721,570	682,979	-38,591
(13)	non-merging firms	6,280,699	6,297,403	16,705
(14)	Consumer surplus (million $)	1681.21	1674.08	-7.13
(15)	Carrier profit (million $)	1266.42	1261.37	-5.05
(16)	Smartphone firm profit (million $)	1116.96	1121.47	4.52
(17)	merged firm	59.68	59.85	0.17
(18)	non-merging firms	1057.28	1061.62	4.34

SA Plot of Estimated Demand and Marginal Cost Shocks

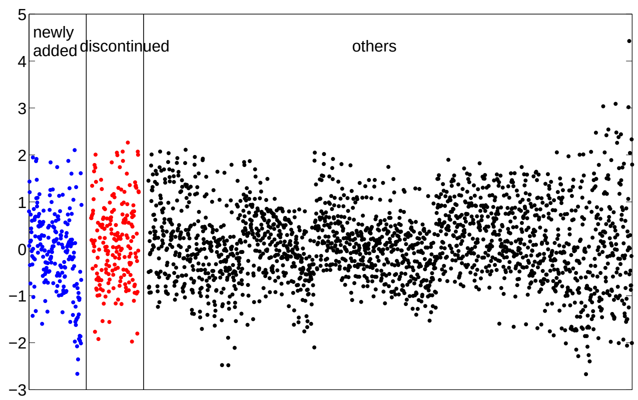
In this section, we plot the estimated demand shocks $\hat{\xi}_{jt}$ and marginal cost shocks $\hat{\eta}_{jt}$ for three groups of observations separately: (1) "newly added": jt s.t. $j \in \mathcal{J}_t$ but $j \notin \mathcal{J}_{t'}, t' < t$; (2) "discontinued": jt s.t. $j \in \mathcal{J}_t$ but $j \notin \mathcal{J}_{t'}$, $t' > t$; and (3) "others": all other jt. Figure SA.1 shows that these three groups do not seem to be very different.

Figure SA.1: Plot of the Estimated Demand Shocks

(a) Demand Shocks



(b) Marginal Cost Shocks



SB Additional Robustness Analyses

In this appendix, we investigate whether our results are robust to additional variations to the demand side and the supply side of the model (in addition to those considered in Section 6). We also estimate a parametric fixed cost function which allows for potential economies or diseconomies of scope in fixed costs.

SB.1 Alternative Demand Specifications

We replace the brand fixed effects by the brand/year fixed effects in one robustness analysis, and include the age of a product (i.e., how long a product has been in the market) and the square of it in the other robustness analysis. Our results are again robust (see Tables SB.1 and SB.2).

SB.2 Alternative Pricing Models

On the supply side, 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 consider another three alternative pricing models.

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

$$\boldsymbol{p} = \left(-\Gamma_c \circ \Delta_c\right)^{-1} \boldsymbol{s} + \left(-\Gamma_m \circ \Delta_m\right)^{-1} \boldsymbol{s} + \tilde{\boldsymbol{mc}}, \tag{SB.1}$$

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

$$\boldsymbol{p} = \left[\left(-\bar{\Gamma}_c \circ \Delta_c\right)^{-1} \boldsymbol{s}\right] \circ \Lambda_c + \left[\left(-\bar{\Gamma}_m \circ \Delta_m\right)^{-1} \boldsymbol{s}\right] \circ \Lambda_m + \tilde{\boldsymbol{mc}}, \tag{SB.2}$$

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 ($\bar{\Gamma}_c = \Gamma_c$, $\bar{\Gamma}_m = \Gamma_m$). 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

$$\Lambda_m(j) = \begin{cases} 1 \text{ if } j \in \text{same non-Apple smartphone firm} \\ 0 \text{ otherwise} \end{cases} \tag{SB.3}$$

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

Table SB.1: Robustness Analysis: Allowing Brand/Year Fixed Effects

(a) Estimation Results

	Parameter	Std. Error
Demand		
Quality coefficient		
battery talk time (hours)	0.056***	0.015
camera resolution (megapixel)	0.092**	0.041
chipset generation 2	0.538***	0.146
chipset generation 3	0.840***	0.199
chipset generation 4	1.142***	0.276
chipset generation 5	1.811***	0.375
screen size (inch)	1	
weight (gram)	-0.003**	0.002
Covariance of random coefficients		
mean	0.530***	0.139
std. dev.	0.340***	0.075
Price	-0.003**	0.002
Flagship?	0.663***	0.063
Brand/year, carrier/year and quarter dummies	Yes	
Marginal Cost ($)		
Exp(quality/10)	463.048***	2.397
Apple	-73.115***	0.128
BlackBerry	89.889***	0.41
Samsung	-29.909***	0.131
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)	-0.67	-3.89	-25.45
Δ(carrier surplus)	-0.50	-2.15	-17.92
Δ(smartphone producer variable profits)	-0.36	-1.70	-2.22
Upper bound of savings in fixed costs	0.63	3.45	22.10

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

	HTC	LG	Motorola	Samsung
Δ(consumer surplus)	2.36	4.19	2.37	4.22
Δ(carrier surplus)	1.18	1.8	1.19	1.82
Δ(smartphone producer variable profits)	0.81	1.14	0.8	1.12
lower bound of added fixed costs	1.92	3.23	1.93	3.25

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

Variable	Pre-merger	Post-merger	Change
Number of products	70	67.40	-2.60
Variety	453.04	440.08	-12.97
Sales-weighted avg quality	10.19	10.23	0.04
Sales-weighted avg price ($)	162.58	166.87	4.29
Total sales	7,433,790	7,355,555	-78,235
Consumer surplus (million $)	3704.08	3650.28	-53.80
Carrier profit (million $)	2650.87	2624.67	-26.19
Smartphone firm profit (million $)	2594.51	2622.01	27.50

Table SB.2: Robustness Analysis: Allowing Age in the Utility Function

(a) Estimation Results

	Parameter	Std. Error
Demand		
Quality coefficient		
battery talk time (hours)	0.046***	0.013
camera resolution (megapixel)	0.091***	0.036
chipset generation 2	0.240***	0.100
chipset generation 3	0.344***	0.131
chipset generation 4	0.461***	0.185
chipset generation 5	0.594**	0.260
screen size (inch)	1	
weight (gram)	0.0004	0.002
Covariance of random coefficients		
mean	0.802***	0.146
std. dev.	0.291***	0.093
Price	-0.238***	0.078
Apple	3.121***	0.113
BlackBerry	1.233***	0.117
Samsung	0.403***	0.070
Flagship?	0.911***	0.081
Age	-0.292***	0.037
Age^2	0.013***	0.003
Carrier/year and quarter dummies	Yes	
Marginal Cost ($)		
Exp(quality/10)	724.827***	2.988
Apple	-13.431***	0.108
BlackBerry	119.201***	0.458
Samsung	-18.228***	0.122
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	Smallest Δ(CS)	Median	Largest
Δ(consumer surplus)	-1.08	-3.36	-10.78
Δ(carrier surplus)	-0.56	-1.66	-6.01
Δ(smartphone producer variable profits)	-0.38	-1.23	-5.41
Upper bound of savings in fixed costs	0.88	2.79	9.83

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

	HTC	LG	Motorola	Samsung
Δ(consumer surplus)	4.11	3.84	4.11	3.84
Δ(carrier surplus)	2.38	1.99	2.4	2.01
Δ(smartphone producer variable profits)	1.9	1.52	1.89	1.51
lower bound of added fixed costs	3.61	3.23	3.62	3.24

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

Variable	Pre-merger	Post-merger	Change
Number of products	70	67.80	-2.20
Variety	310.41	294.20	-16.21
Sales-weighted avg quality	7.96	7.98	0.02
Sales-weighted avg price ($)	76.03	77.16	1.13
Total sales	7,854,756	7,793,287	-61,469
Consumer surplus (million $)	1296.58	1283.22	-13.36
Carrier profit (million $)	1027.46	1019.91	-7.55
Smartphone firm profit (million $)	923.87	929.87	6.00

We now consider three alternative deviations from the baseline model:

Additional Case 1. In this case, smartphone manufacturers decide the retail prices directly. Smartphone firm m's profit maximization problem is:

$$\max_{p_j, j \in \mathcal{J}_m} \sum\nolimits_{j \in \mathcal{J}_m} (p_j - \tilde{mc}_j)\, s_j(\boldsymbol{p}). \tag{SB.4}$$

The first-order condition is equivalent to (SB.2) where $(\Lambda_c = 0, \Lambda_m = 1, \bar{\Gamma}_c = \Gamma_c, \bar{\Gamma}_m = \Gamma_m)$.[29]

Additional Case 2. In this case, carriers choose the retail prices while facing a wholesale price that equals the marginal cost of each product. In other words, carrier c's profit maximization problem is:

$$\max_{p_j, j \in \mathcal{J}_c} \sum\nolimits_{j \in \mathcal{J}_c} (p_j - \tilde{mc}_j)\, s_j(\boldsymbol{p}). \tag{SB.5}$$

The first-order condition is equivalent to (SB.2) where $(\Lambda_c = 1, \Lambda_m = 0, \bar{\Gamma}_c = \Gamma_c, \bar{\Gamma}_m = \Gamma_m)$.

Additional Case 3. In this case, 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:

$$\max_{p_j, j \in \mathcal{J}_{mc}} \underbrace{\sum_{j \in \mathcal{J}_{mc}} \Pi_j(\boldsymbol{p})}_{\text{pair }(m,c)\text{'s profit}} + \underbrace{\mu_m \sum_{j \in \mathcal{J}_m, j \notin \mathcal{J}_c} \tau \Pi_j(\boldsymbol{p})}_{\text{firm } m\text{'s profit from other products}} + \underbrace{\mu_c \sum_{j \in \mathcal{J}_c, j \notin \mathcal{J}_m} (1-\tau)\, \Pi_j(\boldsymbol{p})}_{\text{carrier } c\text{'s profit from other products}}, \tag{SB.6}$$

where $\Pi_j(\boldsymbol{p}) = (p_j - \tilde{mc}_j)\, s_j(\boldsymbol{p})$ is the joint 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

$$\bar{\Gamma}_c(i, j) = \begin{cases} 1 & \text{if } i, j \in \text{same smartphone firm/carrier}, \\ \mu_m \tau & \text{if } i, j \in \text{same smartphone firm, but different carriers}, \\ \mu_c (1-\tau) & \text{if } i, j \in \text{same carrier, but different smartphone firms}, \\ 0 & \text{otherwise}. \end{cases} \tag{SB.7}$$

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

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

Additional Case 1

In this case, the per-unit profit for a carrier is zero and there should be a transfer from a smartphone firm to a carrier. Let T_m be the total transfer that a smartphone firm m pays, $T_{m,\backslash j}$ 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:

$$E_{(\boldsymbol{\xi},\boldsymbol{\eta})}\pi_m\left(\boldsymbol{q},\boldsymbol{\xi},\boldsymbol{\eta}\right) - F_j - T_m \geq E_{(\boldsymbol{\xi}\backslash\xi_j,\boldsymbol{\eta}\backslash\eta_j)}\pi_m\left(\boldsymbol{q}\backslash q_j,\boldsymbol{\xi}\backslash\xi_j,\boldsymbol{\eta}\backslash\eta_j\right) - T_{m,\backslash j} \text{ for any } j \in \mathcal{J}_m \quad \text{(SB.8)}$$
$$E_{(\boldsymbol{\xi},\boldsymbol{\eta})}\pi_m\left(\boldsymbol{q},\boldsymbol{\xi},\boldsymbol{\eta}\right) - T_m \geq E_{(\boldsymbol{\xi}\cup\xi_j,\boldsymbol{\eta}\cup\eta_j)}\pi_m\left(\boldsymbol{q}\cup q_j,\boldsymbol{\xi}\cup\xi_j,\boldsymbol{\eta}\cup\eta_j\right) - F_j - T_{m,\cup j} \text{ for any } j \notin \mathcal{J}_m.$$

The two inequalities in (SB.8) imply that for any $j \in \mathcal{J}_m$,

$$\begin{aligned} F_j &\leq \left[E_{(\boldsymbol{\xi},\boldsymbol{\eta})}\pi_m\left(\boldsymbol{q},\boldsymbol{\xi},\boldsymbol{\eta}\right) - E_{(\boldsymbol{\xi}\backslash\xi_j,\boldsymbol{\eta}\backslash\eta_j)}\pi_m\left(\boldsymbol{q}\backslash q_j,\boldsymbol{\xi}\backslash\xi_j,\boldsymbol{\eta}\backslash\eta_j\right)\right] - \left[T_m - T_{m,\backslash j}\right] \\ &\triangleq \Delta\pi_{m,\backslash j} - \left[T_m - T_{m,\backslash j}\right] \triangleq \bar{F}_j, \end{aligned} \quad \text{(SB.9)}$$

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

$$\begin{aligned} F_j &\geq \left[E_{(\boldsymbol{\xi}\cup\xi_j,\boldsymbol{\eta}\cup\eta_j)}\pi_m\left(\boldsymbol{q}\cup q_j,\boldsymbol{\xi}\cup\xi_j,\boldsymbol{\eta}\cup\eta_j\right) - E_{(\boldsymbol{\xi},\boldsymbol{\eta})}\pi_m\left(\boldsymbol{q},\boldsymbol{\xi},\boldsymbol{\eta}\right)\right] - \left[T_{m,\cup j} - T_m\right] \\ &\triangleq \Delta\pi_{m,\cup j} - \left[T_{m,\cup j} - T_m\right] \triangleq \underline{F}_j. \end{aligned} \quad \text{(SB.10)}$$

These transfers do not affect the equilibrium prices. Therefore, they do not affect consumer surplus or the sum of carriers' variable profit and smartphone firms' variable profits. They do, however, affect our estimates of the fixed cost bounds (see (SB.9) and (SB.10)). We argue that under a reasonable assumption on the transfers, we can obtain an overestimate of the bounds without modeling how the transfers are determined. Specifically, the assumption we need is: the total transfer that a smartphone pays at least weakly increases with the number of its products, i.e.,

Assumption 1 $T_m - T_{m,\backslash j} \geq 0$ *and* $T_{m,\cup j} - T_m \geq 0$.

Under Assumption 1, we have $\bar{F}_j \leq \Delta\pi_{m,\backslash j}$ and $\underline{F}_j \leq \Delta\pi_{m,\cup j}$. We think this assumption is reasonable, in other words, we expect the upper bound (or the lower bound) to be smaller than $\Delta\pi_{m,\backslash j}$ (or $\Delta\pi_{m,\cup j}$). For example, if a carrier shares a portion (denoted by $\varphi \in (0,1)$) of the increase in a smartphone firm's variable profit when a product is added, i.e., $T_m - T_{m,\backslash j} = \varphi\Delta\pi_{m,\backslash j}$ and $T_{m,\cup j} - T_m = \varphi\Delta\pi_{m,\cup j}$, then $\bar{F}_j = (1-\varphi)\Delta\pi_{m,\backslash j} < \Delta\pi_{m,\backslash j}$ and $\underline{F}_j = (1-\varphi)\Delta\pi_{m,\cup j} < \Delta\pi_{m,\cup j}$.

In Table SB.3 where we present the simulation results when a product is removed or added, we report these overestimated bounds: $\Delta\pi_{m,\backslash j}$ and $\Delta\pi_{m,\cup j}$. Table SB.3 shows 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 increases 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.[30]

Table SB.3: Robustness Test, $\Lambda_c = 0, \Lambda_m = 1, \bar{\Gamma}_m = \Gamma_m$

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

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

[a]The 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
Δ(consumer surplus)	2.35	2.40	2.40	2.71
Δ(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

Additional Case 2

In this case, the transfer should be from a carrier to a smartphone instead. Let T_m be the total transfer that a smartphone firm m *receives*, and $T_{m,\backslash j}$ 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:

$$T_m - F_j \geq T_{m,\backslash j} \iff F_j \leq T_m - T_{m,\backslash j} \text{ for any } j \in \mathcal{J}_m \tag{SB.11}$$

$$T_m \geq T_{m,\cup j} - F_j \iff F_j \geq T_{m,\cup j} - T_m \text{ for any } j \notin \mathcal{J}_m. \tag{SB.12}$$

We again make an assumption on the transfers. Specifically, let the changes in the (pre-transfer) profit of j's carrier be:

$$\begin{aligned} \Delta\pi_{c,\backslash j} &= E_{(\boldsymbol{\xi},\boldsymbol{\eta})}\pi_c\left(\boldsymbol{q},\boldsymbol{\xi},\boldsymbol{\eta}\right) - E_{(\boldsymbol{\xi}\backslash\xi_j,\boldsymbol{\eta}\backslash\eta_j)}\pi_c\left(\boldsymbol{q}\backslash q_j,\boldsymbol{\xi}\backslash\xi_j,\boldsymbol{\eta}\backslash\eta_j\right), \\ \Delta\pi_{c,\cup j} &= E_{(\boldsymbol{\xi}\cup\xi_j,\boldsymbol{\eta}\cup\eta_j)}\pi_c\left(\boldsymbol{q}\cup q_j,\boldsymbol{\xi}\cup\xi_j,\boldsymbol{\eta}\cup\eta_j\right) - E_{(\boldsymbol{\xi},\boldsymbol{\eta})}\pi_c\left(\boldsymbol{q},\boldsymbol{\xi},\boldsymbol{\eta}\right). \end{aligned} \tag{SB.13}$$

We assume that 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.,

Assumption 2 $T_m - T_{m,\backslash j} \leq \Delta\pi_{c,\backslash j}$ *and* $T_{m,\cup j} - T_m \leq \Delta\pi_{c,\cup j}$.

[30]We 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.

In Table SB.4, which presents the simulation results in this robustness analysis, we report $\Delta\pi_{c,\setminus j}$ in Table SB.4(a) and $\Delta\pi_{c,\cup j}$ in Table SB.4(b). Under Assumption 2, the bounds of the fixed cost reported in Table SB.4 are again over estimated. Therefore, from Table SB.4, we draw a similar robustness conclusion as in the case of $(\Lambda_c = 0, \Lambda_m = 1, \bar{\Gamma}_m = \Gamma_m)$.

Table SB.4: Robustness Test, $\Lambda_c = 1, \Lambda_m = 0, \bar{\Gamma}_c = \Gamma_c$,

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

Removed product	Lowest-quality	Median	Highest
Δ(consumer surplus)	-0.82	-2.19	-10.65
Δ(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
Δ(consumer surplus)	2.19	2.19	2.19	2.76
Δ(total producer surplus net of fixed costs)	1.06	1.06	1.06	1.42
$\Delta\pi_{c,\cup j}$	2.03	2.03	2.03	2.59

In summary, for the case of $(\Lambda_c = 0, \Lambda_m = 1, \bar{\Gamma}_m = \Gamma_m)$ and $(\Lambda_c = 1, \Lambda_m = 0, \bar{\Gamma}_c = \Gamma_c)$, we argue that under reasonable assumptions on the transfers (between a smartphone firm and a carrier), we can obtain an overestimate of the fixed-cost upper bound and lower bound. The results in Tables SB.3 and SB.4, where we report these overestimated bounds, show that removing a product leads to a decrease in total welfare even considering the (over-estimated) maximum possible saving in the fixed cost and adding a product leads to an increase in total welfare as long as the fixed cost of the added product is not much higher than its (over-estimated) lower bound.

Additional Case 3

We now consider another alternative supply-side model where a smartphone firm and a carrier jointly set the retail price of their products. Specifically, we consider two different choices of (μ_c, μ_m, τ) in equation (SB.6). In this model, how the two parties split the joint profit is determined by the parameter τ, i.e., the share of profit that goes to a smartphone firm. Table SB.5 presents the results, which are again robust.

SB.3 Parametric Fixed Cost Function

So far we assume that the total fixed cost of a firm is the sum of the fixed cost for each product (i.e., there are no economies or diseconomies of scope in fixed costs). Under this assumption, we find that a merger leads to a reduction in product offerings. Is this finding robust to this assumption? Intuitively, if there are diseconomies of scope in fixed costs, the merged firm's per-product fixed cost may increase after the merger, leading to a further reduction in product offerings. If, however,

Table SB.5: 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
Δ(consumer surplus)	-0.85	-1.87	-10.93
Δ(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
Δ(consumer surplus)	1.94	1.93	1.96	2.50
Δ(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

[a]In 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
Δ(consumer surplus)	-0.82	-1.90	-10.90
Δ(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
Δ(consumer surplus)	1.95	1.96	1.97	2.43
Δ(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

there are economies of scope, the merged firm's per-product fixed cost decreases after the merger, which may lead to an increase in product offerings.

To address this concern, we now take a parametric approach and specify a function of the fixed cost allowing for economies or diseconomies of scope as follows:

$$FC_{jt} = \phi_1 q_j + \phi_2 \log\left(n_{m(j)t}\right) + \varphi_{m(j)t}, \tag{SB.14}$$

where q_j is product j's quality index, $n_{m(j)t}$ is the number of products that the smartphone firm $m(j)$ has in period t, and $\varphi_{m(j)t}$ represents the brand/time fixed effects.[31] Note that a negative estimate of the coefficient ϕ_2 indicates economies of scope in fixed costs; and conversely, a positive estimate indicates diseconomies of scope.

Note that the purpose of this exercise is to address the concern that potential economies of scope in fixed costs may lead to an increase in the number of products after a merger, which would be

[31]For notational simplicity, we use j instead of $\tilde{j}$ to represent a product, i.e., we ignore the distinction between j and $\tilde{j}$ as explained in Section 3.2.2.

the opposite of our baseline results. Therefore, our goal in this section is to obtain a (conservative) estimate of the lower bound for ϕ_2. If our conservative estimate of the lower bound is positive (or negative but of small magnitude), then we can conclude that there are diseconomies of scope (or small economies of scope) in fixed costs.

To obtain the estimate of the lower bound for ϕ_2, we consider the following three types of deviations:

(1) Dropping a product j

Nash equilibrium implies that dropping a product does not increase the expected profit of a firm. Let $\Pi_{mt}(\mathcal{J}_{mt}) = E_{(\boldsymbol{\xi}_t,\boldsymbol{\eta}_t)}\pi_{mt}(\boldsymbol{q}_t,\boldsymbol{\xi}_t,\boldsymbol{\eta}_t)$ be the expected profit that a smartphone firm m gets from its observed product portfolio $\mathcal{J}_{mt}$ and $\Pi_{mt}(\mathcal{J}_{mt}\backslash\ j) = E_{(\boldsymbol{\xi}_t\backslash\xi_{jt},\boldsymbol{\eta}_t\backslash\eta_{jt})}\pi_{mt}(\boldsymbol{q}_t\backslash q_j,\boldsymbol{\xi}_t\backslash\xi_{jt},\boldsymbol{\eta}_t\backslash\eta_{jt})$ be that when it drops product j. Then, for any $j\in\mathcal{J}_{mt}$,

$$[\Pi_{mt}(\mathcal{J}_{mt}) - (\phi_1 q_j + \varphi_{mt}) - \phi_2 n_{mt}\log(n_{mt})] - [\Pi_{mt}(\mathcal{J}_{mt}\backslash\ j) - \phi_2(n_{mt}-1)\log(n_{mt}-1)] + \upsilon_{jt} \geq 0,$$

where υ_{jt} is added to the inequality to represent an expectation error that is uncorrelated with product choices (e.g., Holmes (2011) and Pakes, Porter, Ho and Ishii (2015)). Then,

$$\begin{aligned}&\phi_1 q_j + \varphi_{mt} + \phi_2[n_{mt}\log(n_{mt}) - (n_{mt}-1)\log(n_{mt}-1)] \\ \leq\ & \Pi_{mt}(\mathcal{J}_{mt}) - \Pi_{mt}(\mathcal{J}_{mt}\backslash\ j) + \upsilon_{jt}.\end{aligned} \tag{SB.15}$$

(2) Replacing product j by a high-quality product j'

Such a deviation gives us the following inequality:

$$\begin{aligned}&[\Pi_{mt}(\mathcal{J}_{mt}) - (\phi_1 q_j + \varphi_{mt}) - \phi_2 n_{mt}\log(n_{mt})] \\ &-\left[\Pi_{mt}\left(\mathcal{J}_{mt}\backslash\ j\cup j'\right) - \left(\phi_1 q_{j'} + \varphi_{mt}\right) - \phi_2 n_{mt}\log(n_{mt})\right] + \upsilon_{jj't} \geq 0,\end{aligned}$$

implying

$$\phi_1\left(q_{j'} - q_j\right) \geq \Pi_{mt}\left(\mathcal{J}_{mt}\backslash\ j\cup j'\right) - \Pi_{mt}(\mathcal{J}_{mt}) - \upsilon_{jj't}. \tag{SB.16}$$

(3) Replacing product j by two products k_1 and k_2 such that $q_{k1} + q_{k2} = q_j$

Similarly, we have

$$\begin{aligned}&[\Pi_{mt}(\mathcal{J}_{mt}) - (\phi_1 q_j + \varphi_{mt}) - \phi_2 n_{mt}\log(n_{mt})] \\ &-[\Pi_{mt}(\mathcal{J}_{mt}\backslash\ j\cup k_1\cup k_2) - (\phi_1 q_{k_1} + \varphi_{mt}) - (\phi_1 q_{k_2} + \varphi_{mt}) - \phi_2(n_{mt}+1)\log(n_{mt}+1)] + \upsilon_{jk_1k_2t} \geq 0,\end{aligned}$$

implying

$$\begin{aligned}&\varphi_{mt} + \phi_2[(n_{mt}+1)\log(n_{mt}+1) - n_{mt}\log(n_{mt})] \\ \geq\ & \Pi_{mt}(\mathcal{J}_{mt}\backslash\ j\cup k_1\cup k_2) - \Pi_{mt}(\mathcal{J}_{mt}) - \upsilon_{jk_1k_2t}.\end{aligned} \tag{SB.17}$$

To obtain a conservative lower bound for ϕ_2, we take the difference of (SB.17) and (SB.15) and obtain

$$\begin{aligned}
& \phi_2 \left[(n_{mt}+1)\log(n_{mt}+1) - 2n_{mt}\log(n_{mt}) + n_{mt}\log(n_{mt})\right] && \text{(SB.18)} \\
\geq\; & \left[\Pi_{mt}(\mathcal{J}_{mt} \backslash\, j \cup k_1 \cup k_2) - \Pi_{mt}(\mathcal{J}_{mt})\right] - \left[\Pi_{mt}(\mathcal{J}_{mt}) - \Pi_{mt}(\mathcal{J}_{mt} \backslash\, j)\right] + \phi_1 q_j - \upsilon_{jt} - \upsilon_{jk_1k_2t} \\
\geq\; & \left[\Pi_{mt}(\mathcal{J}_{mt} \backslash\, j \cup k_1 \cup k_2) - \Pi_{mt}(\mathcal{J}_{mt})\right] - \left[\Pi_{mt}(\mathcal{J}_{mt}) - \Pi_{mt}(\mathcal{J}_{mt} \backslash\, j)\right] \\
& + \frac{\Pi_{mt}(\mathcal{J}_{mt} \backslash\, j \cup j') - \Pi_{mt}(\mathcal{J}_{mt})}{q_{j'} - q_j} q_j - \upsilon_{jt} - \upsilon_{jk_1k_2t} - \frac{q_j}{q_{j'} - q_j}\upsilon_{jj't},
\end{aligned}$$

where the second inequality is obtained by plugging (SB.16) into the first inequality. This inequality eventually gives us

$$\begin{aligned}
\phi_2 \;\geq\; & \frac{\left[\Pi_{mt}(\mathcal{J}_{mt} \backslash\, j \cup k_1 \cup k_2) - \Pi_{mt}(\mathcal{J}_{mt})\right] - \left[\Pi_{mt}(\mathcal{J}_{mt}) - \Pi_{mt}(\mathcal{J}_{mt} \backslash\, j)\right] + \frac{\Pi_{mt}(\mathcal{J}_{mt} \backslash\, j \cup j') - \Pi_{mt}(\mathcal{J}_{mt})}{q_{j'} - q_j} q_j}{\left[(n_{mt}+1)\log(n_{mt}+1) - 2n_{mt}\log(n_{mt}) + n_{mt}\log(n_{mt})\right]} \\
& - \frac{-\upsilon_{jt} - \upsilon_{jk_1k_2t} - \frac{q_j}{q_{j'}-q_j}\upsilon_{jj't}}{\left[(n_{mt}+1)\log(n_{mt}+1) - 2n_{mt}\log(n_{mt}) + n_{mt}\log(n_{mt})\right]}. \\
\triangleq\; & \Phi_{jt} + \epsilon_{jt}, && \text{(SB.19)}
\end{aligned}$$

We denote the first line in (SB.19) by Φ_{jt}, and with a slight abuse of notation, the second line by ϵ_{jt}.[32] As mentioned, we assume that ϵ_{jt} is uncorrelated with product choices. Then, we have

$$\phi_2 \geq E\Phi_{jt}. \tag{SB.20}$$

In estimation, we set the quality difference $q_{j'} - q_j$ in (SB.16) to be 0.05, and $q_{k1} = 0.4q_j$ and $q_{k2} = 0.6q_j$ in (SB.17).[33] According to our estimate, the lower bound of the estimated set for ϕ_2 is $\frac{1}{\#\mathcal{J}}\sum_{jt\in\mathcal{J}}\Phi_{jt} = 0.017$. Following Imbens and Manski (2004), the lower bound of the 95% confidence interval for ϕ_2 is $\frac{1}{\#\mathcal{J}}\sum_{jt\in\mathcal{J}}\Phi_{jt} - \frac{\sqrt{\widehat{var}(\Phi_{jt})}}{\sqrt{\#\mathcal{J}}}c_{0.05} = 0.016$, where $\widehat{var}(\Phi_{jt})$ is an estimator of the variance of Φ_{jt} and $c_{0.05}$ represents the critical value. These results suggest that there are some diseconomies of scope in fixed costs. For example, $\phi_2 = 0.017$ means that, for the merged firm Samsung-LG, when it drops a product, the fixed cost for each of its remaining products decreases by 1.6 million dollars. Therefore, if anything, we underestimate the decrease in product offerings in our baseline results.

SC Δ(Consumer Surplus) without Changes in Logit Errors

One concern with our finding that removing (or adding) a product leads a decrease (or an increase) in total welfare is that we may overestimate the consumer surplus changes because when

[32] As will be explained later, in the estimation, we choose $q_{j'}$, q_{k_1} and q_{k_2} as a constant function of q_j. As the result, the second summand in (SB.19) is only jt specific.

[33] The results are robust to other choices of $q_{j'} - q_j$ and (q_{k1}, q_{k2}).

we remove (or add) a product, we remove (or add) the logit error term corresponding to this product, which is independent of other logit error terms. To address this concern, in this section, we recalculate Δ(consumer surplus) without removing or adding a logit error term. Specifically, when product j is added to a set of existing products $\mathcal{J}_t$, we assign the logit error of an existing product $k \in \mathcal{J}_t$ to the added product j so that there is no added logit error term. We choose product k to be the closest to j's quality among all existing products of j's manufacturer.[34] We take a similar approach for the case of removing a product. Note that when product j is removed from the set $\mathcal{J}_t$, the decrease in consumer surplus is essentially the increase in consumer surplus when product j is added to the set $\mathcal{J}_t \backslash j$.

With this alternative measure of consumer surplus, Tables 7 (removing a product) and 8 (adding a product) become:

Table SC.1: Welfare Changes When a Product Is Removed, March 2013 (million $)

Removed product	Lowest-quality	Median	Highest
Δ(consumer surplus without changes in logit errors)	-0.46	-1.51	-10.35
Δ(carrier surplus)	-0.83	-1.39	-9.13
Δ(smartphone producer variable profits)	-0.50	-0.90	-3.24
Upper bound of savings in fixed costs	0.94	2.19	12.14
Rows 1+2+3+4	-0.45	-0.54	-8.12

Table SC.2: Welfare Changes When a Product Is Added, March 2013 (million $)

	HTC	LG	Motorola	Samsung
Δ(consumer surplus without changes in logit errors)	1.11	1.26	1.38	2.09
Δ(carrier surplus)	1.26	1.27	1.29	1.53
Δ(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
(Rows 1+2+3)/(Row 4)	1.62	1.69	1.72	2.01

The changes in consumer surplus are indeed smaller than what are reported in Tables 7 and 8. However, the sum of the four rows in Table SC.1 is still negative, and the ratio of the first three rows to the last row in Table SC.2 varies between 1.62 and 2.01, still larger than then benchmark number 1.2 (see Section 5.1).

SD 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

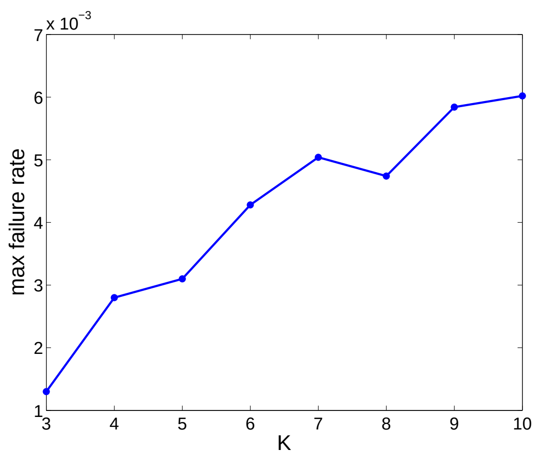
[34] We could also set the logit error of the removed product to be zero. However, since our estimates are based on a model with logit errors, doing so means that we cannot match the market share data. Our approach allows us to get rid of the effect of adding an independent logit error term while being close to our data.

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 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.[35] 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.

We repeat the above Monte Carlo simulations for the numbers of potential products $K = 3, .., 10$. In Figure SD.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 SD.1 shows that, as the number of potential products (K) increases, so does the maximum failure rate.[36] 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 SD.1: Failure Rate of the Heuristic Algorithm



[35] We 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 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.

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