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

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May 18, 2016

Abstract

In this paper, we study (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. We find that there are too few products and a reduction in competition further decreases the number of products and reduces product variety. These results suggest that merger policies should be stricter when we take into account the effects of a merger on product choice in addition to those on pricing.

Key words: endogenous product choice, product proliferation, merger, smartphone industry
JEL Classifications: L13, L15, L41, L63

1 Introduction

In many markets such as the printer market, the CPU market and the smartphone market, firms typically offer multiple products across a wide spectrum of quality. In these markets, product proliferation is an outcome of firms' oligopolistic competition in product space. Does such competition result in too few or too many products from a welfare point of view? How does a change in competition affect the number and the 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, both excessive and insufficient product proliferation are possible. On the one hand, a profit-maximizing firm will have a product in the market as long as the profit

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gains are greater than the costs, but some of the profit gains may come from business stealing. Because firms do not take into account this negative externality, there may be too many products. On the other hand, unlike a social planner, firms do not internalize consumer surplus. If consumer surplus increases when a product is added to the market, there may also be too few products. Therefore, whether there are too few or too many products in the market is an empirical question.

Secondly, 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 put fewer products in the market. This is a direct effect. However, there may also exist a countervailing indirect effect: a merger is likely to soften the price competition, which may lead to higher prices. As a result, the profit gains from adding a product may be larger, leading to more products in the market.

Combining these two research questions, this paper sheds light on how to adjust the leniency of competition policies when product offerings are endogenous. If competition leads to too many products and a merger reduces product offerings, then merger policies should be more lenient because the consumer welfare loss due to reduced product offerings may be offset by the savings of fixed costs in producer surplus. Conversely, merger policies should be stricter if a merger reduces product offerings when there are already too few products in the market.

As mentioned, we study these questions on product proliferation 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. The worldwide smartphone sales grew from 122 million units in 2007 to 1.4 billion units in 2015 (Gartner (2007) and Gartner (2015)). Global revenue was about 400 billion dollars in 2015 (GfK (2016)). Moreover, product proliferation is a prominent feature of this industry. For example, Samsung on average offered 13 smartphones in the U.S. market in a given month during our sample period (January 2009 to March 2013). These products vary substantially in their qualities and prices. Such a pattern is also true for most other firms.

In order to address our research questions and quantify welfare, we develop a structural model of consumer demand and firms' product and price decisions. The demand side is described by a random coefficient discrete choice model, in which the quality of a product is a linear function of a set of key product characteristics, and consumers have heterogeneous tastes for quality. The supply side is captured by a static three-stage structural model. In the first stage, smartphone firms choose products from a set of potential products. For each product in each period, there is a fixed cost of having this product in the market. In the second stage, after observing the product portfolios of each firm as well as the realized demand and marginal cost shocks for each product, firms set the wholesale prices for carriers. Finally, carriers set the retail prices for consumers in the third stage.

Our data come from the Investment Technology Group (ITG) Market Research. This data set provides information on all smartphones in the U.S. market between January 2009 and March 2013. For every month during this period, we observe the price and the quantity of each smartphone sold

through each of the four national carriers in the U.S. (i.e., AT&T, T-Mobile, Sprint and Verizon). We also observe key specifications of each product, such as battery talk time and camera resolution.

Using these data, we estimate the model of smartphone demand and marginal cost following an estimation procedure similar to that in Berry, Levinsohn and Pakes (1995). The estimation results are intuitive: on average, consumers prefer smartphones with longer battery talk time, higher camera resolution, a more advanced chipset, a larger screen and lighter weight. We refer to a linear combination of product characteristics, where the weights are given by the estimated demand coefficients of these characteristics, as the quality index of a product. We allow for a random coefficient on this quality index and find that the estimated standard deviation of this random coefficient is about 1/3 of its mean, indicating that consumers are heterogenous in their willingness-to-pay for quality. On the supply side, we find that marginal cost increases in quality and decreases over time.

We also obtain bounds on fixed costs using the optimality conditions related to firms' product choice decisions. Specifically, because we assume that the observed product portfolio of a firm is profit maximizing in a Nash equilibrium, removing a product 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 can 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 first 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 of our data. We remove products in one set of counterfactual simulations and add products in the other. To separate the issue of product variety – the focus of this paper – from the issue of innovation, we only remove or add products below the quality frontier of each firm.[1] We find that when a product is removed, even considering the maximum saving in the fixed cost, total surplus decreases. 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 and carrier surplus, and smartphone firms' total variable profit all increase. For this added product, we have obtained a lower bound on its fixed cost. When we compare this lower bound with the sum of the increases in consumer surplus, carrier surplus and smartphone firms' total variable profit, we find that the latter is more than 2.3 times of the former. Therefore, as long as the fixed cost is not more than 2.3 times of its lower bound, total surplus would increase with the increased product offerings. To put the number 2.3 in perspective, note that the average upper bound is about 1.2 times of the average lower bound we obtain in the estimation. Overall, these counterfactual simulation results suggest that there are too few products.

[1] See Yang (2015) for a study on innovation in the smartphone industry and its upstream chipset industry.

Turning to the second research question of how competition affects product offerings, we simulate the effect of a hypothetical merger between Samsung and LG in March 2013, which are the second and the third largest smartphone firms in terms of sales in that month. We also repeat the simulation for a Samsung-Motorola merger and a LG-Motorola merger, where Motorola is the fourth largest smartphone firm in March 2013. Again, to separate product variety from innovation, we allow firms to adjust only products below their quality frontier. But 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 be the firm's products in either February 2013 or March 2013, plus 8 additional products that vary in quality. However, even with this restriction on the set of potential products, a firm's action space can still be prohibitively large. For example, the merged Samsung-LG has 44 potential products. It can choose any subset (of any size) of these 44 products, implying a choice set of 2^{44} ($\approx 1.8 \times 10^{13}$) product portfolios. 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. In applying this algorithm, we start from a product portfolio and compute a firm's profit from dropping *one* product from or adding *one* potential product to this portfolio. If no such deviation is profitable, we stop. Otherwise, starting from the most-profitable deviating product portfolio from in the previous step, we again ask whether the firm's profit can increase by adding or dropping one product. We continue this process until the firm's profit does not increase by such a one-product deviation any more.

Note that even though a firm is restricted to use one-product deviations in each step of the algorithm, the firm can make large changes to its product portfolio over multiple steps. To evaluate the performance of this algorithm, we conduct Monte Carlo simulations to evaluate the performance of this algorithm and show that it does well at least for optimal product portfolio problems with a small number of potential products.[2]

Using this algorithm, we find that after the Samsung-LG merger, the product offerings in the market decrease. In particular, the merged firm drops 3 products out of its 27 products before the merger, and the competing firms sometimes add one product in total. To measure the resulting effect on product variety, we propose a measure of product variety that resembles a CES utility function. We find that, in the end, there is a decrease in product variety. Due to the

[2]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 0.3% regardless of the starting point for the heuristic algorithm.

decreased product offerings and increases in the prices, consumers are worse off and total welfare also decreases. These findings hold for the other two mergers (Samsung-Motorola and LG-Motorola) as well.

In summary, we find that there are too few products in the market, and a reduction in competition further decreases the product offerings. These findings are robust to several variations to the demand side or the supply side of the model. The combination of these findings suggests that merger policies may have to be stricter when we take into account the effect of a merger on product offerings in addition to its effect on prices.

By studying the welfare implications of product proliferation and how competition affects them, this paper contributes to the literature of endogenous product choice. Examples in this literature include Draganska, Mazzeo and Seim (2009), Fan (2013), Sweeting (2013), Eizenberg (2014), Crawford, Shcherbakov and Shum (2015) and Berry, Eizenberg and Waldfogel (forthcoming).[3] Among these papers, Fan (2013) and Berry, Eizenberg and Waldfogel (forthcoming) are most closely related to this paper. Fan (2013) also studies the effect of a merger considering firms' endogenous product choice. However, different from Fan (2013) which keeps the number of products fixed, in our paper, this paper allows firms to adjust both the number and the composition of products after a merger. Berry, Eizenberg and Waldfogel (forthcoming) is also closely related to this paper as it also studies whether there is too little or too much product variety. However, different from their paper, which studies the local radio market where firms are *single*-product firms and thus excessive product variety is related to excessive firm entry, product variety in our setting is determined by not only the set of firms in the market, but also each firm's product choice given the market structure. We also obtain different results. While they find too much product variety in the local radio market, we find too few products in the U.S. smartphone industry. This difference in the results may be related to the difference in the market structure. Compared to a single-product firm, a multiple-product firm has an additional reason for not adding a product: to avoid cannibalization. As a result, in a market with multiple-product firms, it is more likely that there are too few products.

This paper is also related to an empirical literature studying the smartphone industry. For example, Sinkinson (2014) studies the motivations for the exclusive contract between Apple and AT&T for the early iPhones. Zhu, Liu and Chintagunta (2015) quantify the welfare effect of such an exclusive contract. Luo (2015) studies the operation system network effect. Finally, Yang (2015) 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

[3] Other examples in this literature include Seim (2006), Watson (2009), Chu (2010), Crawford and Yurukoglu (2012), Nosko (2014) and Wollmann (2015). 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 (forthcoming).

the model of the smartphone market in Section 3 and present the estimation results in Section 4. Section 5 describes counterfactual simulations and shows 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 the given carrier in the given 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: it is the average price for a smartphone device that a carrier charges a consumer who uses this carrier's network service.[4] The subsidized price for a smartphone is not the true cost of buying a smartphone from a consumer's perspective because the consumer also needs to pay for the service plan. As will be explained later, we therefore include carrier/year-specific fixed effects to capture the average service cost for a consumer. The price information for carriers other than the four major national carriers (for example, Boost and MetroPCS) is unsubsidized, as these carriers very often provide only prepaid service plans. In addition, these carriers usually serve only one regional market. For these reasons, we drop observations of these fringe carriers.[5]

In the end, our sample consists of 3256 observations, each of which is a smartphone/carrier/month combination. There are 18 firms and 266 smartphones in the sample. The majority of smartphones (88%) are sold through one carrier. Moreover, when the same smartphone is sold through different carriers, it is often pre-installed with different softwares and sometimes have different weight. For these reasons, we define a product as a smartphone/carrier combination.

Table 1 presents the summary statistics on quantity, price and product characteristics. From Table 1, we can see that the average monthly sales of a product is around 77,000 while the standard deviation of the monthly sales is about twice the mean, suggesting a large dispersion in the sales of products. There is also a sizable variation in price across observations: the price is 122 dollars on average, with a standard deviation of 85. For each product, we observe product characteristics such as battery talk time, camera resolution, screen size measured by the diagonal of the screen, and weight. We also observe the generation of the chipset used by each product. For example,

[4]The average is taken over transactions in a month. Note that the carrier fee structure has been relatively stable during our sample period. In April 2013, however, T-Mobile launched an "Uncarrier" campaign, which abandoned service contracts and subsidies for devices. Consumers are asked to buy a device outright, or through a device installment plan. Other carriers followed suit after T-Mobile made this change.

[5]The total market share of these fringe carriers in terms of smartphones sold is about 10%.

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. Table 1 reports summary statistics of these product characteristics. Their standard deviations are about 17% to 47% of the corresponding means, indicating that the market has a wide variety of products.

Table 1: Summary Statistics

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

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

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

Table 2 lists the top six firms according to their average monthly smartphone sales: Apple, Samsung, BlackBerry, HTC, Motorola and LG. Among them, Apple is the undisputed leader in the industry, with an average monthly sales of about 2 million units. It is followed by Samsung, whose average monthly sales is 0.76 million. The table also shows that all of these six firms offer multiple products simultaneously. For example, on average, Samsung has 13 products in a given month, followed by BlackBerry and HTC with an average of 11 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	3.94
Samsung	Korea	0.76	13.20
BlackBerry	Canada	0.61	11.31
HTC	Taiwan	0.60	11.90
Motorola	U.S.	0.46	7.90
LG	Korea	0.33	7.19

[a] Averaged across months.

The multiple products offered by a firm have different qualities and prices, as shown by Table 3 on the within-(firm/month) dispersion of price and product characteristics. In Table 3, we report two dispersion measures: standard deviation and range. Take price as an example: for each firm/month, we compute the standard deviation of price across all products offered by the given

firm in the given month. We set the standard deviation to 0 for firm/months with a single product. We then take the average of these standard deviations across all 577 firm/months, and report it in Column 1 of Table 3. Similarly, we compute the difference between the highest and the lowest price among all products in the same firm/month, take the average across firm/months, and report it as the average range within a firm/month in Column 2 of Table 3. The table shows that the average within-firm/month standard deviation in price is 42.42 dollars, which is about 1/3 of the average price in the data, and about 1/2 of the standard deviation of price across all observations (see Table 1), implying that the within firm/month variation in price is an important component of its total variation. The average range of the price within the same firm/month is as high as 123 dollars. The within firm variation of product characteristics is also significant. For example, looking at the range of the chipset generation, we can see that smartphone firms on average simultaneously offer products whose chipsets are one generation apart. Overall, Table 3 provides evidence on product proliferation in this industry. In the next section, we set up a model to describe how firms choose their products and the prices of their products.

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

	Average Std. Dev.	Average Range
Price ($)	42.42	122.5
Battery talk time (hours)	1.04	3.10
Camera resolution (megapixel)	0.81	2.16
Chipset generation	0.36	0.93
Screen size (inch)	0.21	0.61
Weight (gram)	11.12	32.23

3 Model

3.1 Demand

The demand is described by a random-coefficient discrete choice model. In the model, a consumer chooses a smartphone product or the outside option of no purchase. The utility that consumer i gets from purchasing product j in period t is assumed to be

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

where q_j is a quality index of product j. It depends on the observable product characteristics $\boldsymbol{x}_j$ as $q_j = \boldsymbol{x}_j \boldsymbol{\beta}$, where $\boldsymbol{\beta}$ are parameters to be estimated. The random coefficient β_i captures consumers' heterogeneous tastes for quality. It is assumed to follow a normal distribution with mean β_0 and variance σ^2. Since we cannot separately identify the scales of β_0, σ and $\boldsymbol{\beta}$, we normalize the first dimension of $\boldsymbol{\beta}$ to be 1. The price of product j in period t is denoted by p_{jt}.

We include brand fixed effects, carrier/year fixed effects and quarter fixed effects in the utility function. The brand fixed effect captures consumers' average taste for a brand. We denote the brand fixed effect by $\lambda_{m(j)}$, where $m(j)$ represents the smartphone firm of j. The carrier/year fixed effect captures the average quality and the cost of carrier c's network service in period t as well as a general time trend in consumers' tastes for smartphones.[6] We also include quarter fixed effects to capture seasonality in demand. 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 product j. The term ξ_{jt} is a demand shock. Finally, 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}, the market share of product j in period t is

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

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

Following Berry, Levinsohn and Pakes (1995), we define the mean utility of product 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).

3.2 Supply

The supply side of the model is described by a static three-stage game. In the first stage, firms choose their products. Next, after observing the demand and the marginal cost shocks, firms choose the wholesale prices charged to the carriers. Finally, carriers chooses subsidized retail prices. We describe these three stages in reverse order.

3.2.1 Decisions on Prices

At the third stage, carriers observe the set of products available on each carrier (denoted by $\mathcal{J}_{ct}$), the wholesale prices (w_{jt}) and the demand shocks (ξ_{jt}). They choose the retail prices (p_{jt}) to

[6] By using fixed effects to capture the features and the prices of carriers' service plans, 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. That is, it is plausible to assume that carriers' service plans are exogenous to smartphone firms' product and price decisions.

maximize their respective profit. Suppose that the profit that carrier c obtains through its service is b_{ct} per consumer. Carrier c's profit margin for each unit of product j sold is therefore $p_{jt}+b_{ct}-w_{jt}$. We do not observe b_{ct} or ω_{jt}. But we can invert out $\tilde{w}_{jt}=w_{jt}-b_{c(j)t}$ from the first-order condition on the price p_{jt}. Specifically, carrier c's profit-maximizing problem is

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

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

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

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 $p_{jt}^{*}\left(\tilde{\boldsymbol{w}}_t,\boldsymbol{q}_t,\boldsymbol{\xi}_t\right)$, where $\tilde{\boldsymbol{w}}_t=(\tilde{\boldsymbol{w}}_{jt},j\in\mathcal{J}_t)$, and $\boldsymbol{q}_t$ and $\boldsymbol{\xi}_t$ have been analogously defined in Section 3.1.

At the second stage, smartphone firms choose the wholesale prices that they charge carriers after observing the demand shocks and the marginal cost shocks. We assume that the marginal cost of a product depends on its quality, time fixed effects, and a product/time-specific shock.[7] Specifically, we assume that the marginal cost is $mc_{jt}=\gamma_t+\gamma_1 exp\left(q_j\right)+\omega_{jt}$. Let $\tilde{mc}_{jt}=mc_{jt}-b_{c(j)t}$, and $\tilde{\gamma}_{ct}=\gamma_t-b_{ct}$. With these notations, we can re-write the marginal cost as

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

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

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

where $\mathcal{J}_{mt}$ represents its product portfolio. The first-order condition is

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

or equivalently,

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

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

[7] Note that a product is a smartphone/carrier combination. Marginal costs may vary across carriers because different radio technologies are used for products sold by different carriers. Moreover, carriers sometimes require firms to preload different softwares on a smartphone, which may come with different costs.

$\left(\sum_{j''\in\mathcal{J}_t}\frac{\partial s_{j't}}{\partial p_{j''t}}\frac{\partial p^*_{j''t}}{\partial\tilde{w}_{jt}}\right)$. Combining equations (5) and (9) yields

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

which we bring to the data for estimation.

3.2.2 Decisions on Products

At the first-stage of the model, firms choose products. Smartphone firms typically offer a few flagship products and a set of non-flagship products. For example, Samsung's Galaxy S series products are its flagship products while other Samsung products are non-flagship products. In total, there are 36 flagship smartphones in our data.[8] Flagship products are usually equipped with the cutting-edge technologies. A firm typically needs to pay a sizable sunk cost of innovation to develop such products. Therefore, to separate the issue of product variety from the issue of innovation, at this stage of the model, we take the set of flagship products in the market as given, and focus on how firms choose their non-flagship products.[9]

There is a fixed cost for every product, denoted by F_{jt}. Since non-flagship products are behind the technology frontier, we assume that there is no sunk cost of introducing a new non-flagship product. There is only a (flow) fixed cost that occurs every period. Therefore, similar to Eizenberg (2014), for example, we treat the product choice as static. Nash equilibrium implies that given competitors' product portfolios at the equilibrium, any deviation from a firm's equilibrium product portfolio should generate a lower or equal expected profit for this firm, where the expectation is taken over the demand shocks and the marginal cost shocks. Specifically, we consider two types of deviations: removing a product in the data or adding a product not in the data. For both types of deviations, we restrict the product to be a non-flagship product.

First, firm m's expected profit should not increase if product j in its portfolio is removed, i.e.,

$$E_{(\boldsymbol{\xi}_t,\boldsymbol{\omega}_t)}\pi_{mt}\left(\boldsymbol{q}_t,\boldsymbol{\xi}_t,\boldsymbol{\omega}_t\right)-F_{jt}\geq E_{(\boldsymbol{\xi}_t,\boldsymbol{\omega}_t)}\pi_{mt}\left(\boldsymbol{q}_t\backslash q_j,\boldsymbol{\xi}_t\backslash\xi_{jt},\boldsymbol{\omega}_t\backslash\omega_{jt}\right)\text{ for any } j\in\mathcal{J}_{mt}, \tag{11}$$

where $\pi_{mt}\left(\boldsymbol{q}_t,\boldsymbol{\xi}_t,\boldsymbol{\omega}_t\right)$ is the equilibrium variable profit (at the stage-2 and stage-3 pricing equilibrium) for firm m. Inequality (11) gives an upper bound of F_{jt} for jt in the data. Intuitively, for products in the market, their fixed costs should be bounded from above.

Second, firm m's expected profit should be lower or equal if a potential product j such that

[8]See Appendix A for a list of these 36 flagship smartphones in our data.

[9]Moreover, flagship products are sold globally. Studying firms' decisions on them therefore requires us to make the assumption that the demand function estimated using the U.S. data captures the global demand well. In other words, we need to rule out substantial cross-country variation in either the set of products offered in a country or the consumer taste. In contrast, non-flagship products are behind the technological frontier and are tailored to the U.S. market rather than sold globally. Having data on the U.S. market is enough to study firms' product-choice decisions about them.

$j \notin \mathcal{J}_{mt}$ is added to its product portfolio. The corresponding inequality is

$$E_{(\boldsymbol{\xi}_t,\boldsymbol{\omega}_t)}\pi_{mt}\left(\boldsymbol{q}_t,\boldsymbol{\xi}_t,\boldsymbol{\omega}_t\right) \geq E_{(\boldsymbol{\xi}_t,\boldsymbol{\omega}_t)}\pi_{mt}\left(\boldsymbol{q}_t \cup q_j,\boldsymbol{\xi} \cup \xi_{jt},\boldsymbol{\omega}_t \cup \omega_{jt}\right) - F_{jt} \text{ for any } j \notin \mathcal{J}_{mt}. \tag{12}$$

This inequality yields a lower bound of F_{jt} for any jt such that $j \notin \mathcal{J}_t$. This is again intuitive because the fixed cost of a not-offered product should be sufficiently high and bounded from below. Note that such a potential product j can be any product not in the data. In Sections 4 and 5, we will 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 cost 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 characteristics of other products of the same firm or products of other firms. We also 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. Similar to Berry, Levinsohn and Pakes (1995), this estimation strategy relies on the timing assumption that the shocks are realized after the product choice. Note that we control for the systematic brand effects, carrier effects and time effects using various fixed effects. Therefore, it seems reasonable (though imperfect) to assume that the product- and time-specific shocks are realized after the products are chosen.

As for the fixed cost, we use inequalities (11) and (12) to obtain the bounds. As mentioned, we apply these two inequalities only to non-flagship products. Therefore, for simplicity of exposition, in the rest of the paper, whenever we discuss fixed-cost bounds, we mean those for a non-flagship product. We obtain an upper bound of the fixed cost for products in the market using inequality (11). The upper bound of F_{jt} is (the opposite of) the change in the expected variable profit when product j is removed, i.e., $E_{(\boldsymbol{\xi}_t,\boldsymbol{\omega}_t)}\pi_{mt}\left(\boldsymbol{q}_t,\boldsymbol{\xi}_t,\boldsymbol{\omega}_t\right) - E_{(\boldsymbol{\xi}_t,\boldsymbol{\omega}_t)}\pi_{mt}\left(\boldsymbol{q}_t \backslash q_j,\boldsymbol{\xi}_t \backslash \xi_{jt},\boldsymbol{\omega}_t \backslash \omega_{jt}\right)$. The expectation is taken over the demand and the marginal cost shocks $(\boldsymbol{\xi}_t,\boldsymbol{\omega}_t)$. We assume that they each follow a normal distribution. We obtain the estimates of the means and the standard deviations based on the estimated $(\hat{\boldsymbol{\xi}}_t,\hat{\boldsymbol{\omega}}_t)$. To compute the expected variable profit, we draw these shocks from their respective estimated distributions, compute the pricing equilibrium for each draw and then calculate the resulting variable profit for firm m. Finally, we take the average of these variable profits across all draws. We obtain the lower bound of the fixed cost F_{jt} for any jt such that $j \notin \mathcal{J}_t$ following a similar procedure based on inequality (12).

4.2 Estimation Results

Table 4 reports the estimation results on demand and marginal cost. The estimation results indicate that consumers on average favor products with longer battery talk time, higher camera resolution, a more advanced chipset, and a larger screen. For example, an increase in the battery

Table 4: Estimation Results

	Parameter	Std. Error
Demand		
Quality coefficient		
Battery talk time (hours)	0.048***	0.013
Camera resolution (megapixel)	0.084***	0.036
Chipset generation 2	0.464***	0.114
Chipset generation 3	0.711***	0.147
Chipset generation 4	1.110***	0.204
Chipset generation 5	1.700***	0.282
Screen size (inch)	1	
Weight (gram)	-0.001	0.001
Quality random coefficient		
Mean	0.805***	0.128
Std. Dev.	0.272***	0.081
Price	-0.007***	0.002
Apple	2.729***	0.092
BlackBerry	1.217***	0.120
Samsung	0.322***	0.068
Flagship?	0.672***	0.066
Carrier/year and quarter dummies	Yes	
Marginal Cost ($)		
Exp(quality/10)	519.773***	2.167
Apple	-25.261***	0.105
BlackBerry	98.355***	0.375
Samsung	-19.639***	0.116
Carrier/year dummies	Yes	

*** indicates 99% level of significance.

talk time by one hour is equivalent to a decrease in the price by 5.9 dollars for an average consumer. Similarly, an increase in the camera resolution by 1 megapixel is equivalent to a decrease in the price by 10 dollars, and an increase in the screen size by 0.1 inch is equivalent to a decrease in the price by 12 dollars. Each generation upgrade is equivalent to a price drop by 30 to 72 dollars. The estimation results also suggest that, *ceteris paribus*, consumers on average prefer a lighter smartphone, though the estimate of this coefficient is statistically insignificant. The estimated standard deviation of consumers' taste for quality is about 1/3 of the average taste, suggesting that consumers are heterogenous in their willingness-to-pay for quality. We include three brand dummies (Apple, BlackBerry and Samsung) and group all other brands as the baseline brand in the

utility function. According to our estimates, there is a large Apple premium (418 dollars), followed by BlackBerry and then Samsung.[10] Our estimation results also suggest that there is an advantage to be a flagship product, which is probably related to firms' differential advertising spending on flagship versus non-flagship products.

Table 5 reports the price semi-elasticities for five top-sales products on AT&T in March 2013.[11] These five products are Motorola's Atrix HD, Samsung's Galaxy S III and Apple's iPhone 4, iPhone 4s and iPhone 5. In Table 5, the entry in Row i and Column j gives the percentage change in market share of product j with a \$10 change in product i's retail price. For example, the diagonal indicates that a \$10 increase of the price of a product leads to about 6% decrease in its demand. Unsurprisingly, the own price semi-elasticities are larger than the cross semi-elasticities.

Table 5: Demand Semi-Elasticities with Respect to Price

	Atrix HD	Galaxy S III	iPhone 4	iPhone 4s	iPhone 5
Atrix HD	-6.467	0.082	0.147	0.196	0.364
Galaxy S III	0.059	-6.439	0.150	0.200	0.375
iPhone 4	0.043	0.060	-6.398	0.161	0.284
iPhone 4s	0.048	0.067	0.134	-6.351	0.310
iPhone 5	0.053	0.076	0.142	0.187	-6.181

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

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. Across all five products, we see that a 1% increase in the quality index corresponds to about 5% to 8% increase in sales.

Table 6: Demand Elasticities with Respect to Quality

	Atrix HD	Galaxy S III	iPhone 4	iPhone 4s	iPhone 5
Atrix HD	7.704	-0.114	-0.135	-0.205	-0.445
Galaxy S III	-0.080	8.030	-0.138	-0.211	-0.461
iPhone 4	-0.054	-0.080	5.043	-0.159	-0.328
iPhone 4s	-0.061	-0.090	-0.118	5.804	-0.365
iPhone 5	-0.070	-0.104	-0.128	-0.193	6.645

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

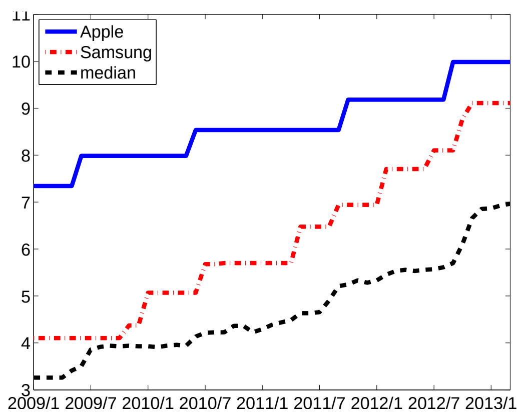
To see the evolution of smartphone quality over time, we divide the brand fixed effects by the mean taste for quality and then add it to the quality index. In Figure 1, we plot the maximum

[10] 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 the sample.

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

and the median of this index across all products in each month. We also plot the maximum of this index for Apple and Samsung. Figure 1 shows that the Apple quality frontier line perfectly coincides with the industry quality frontier line; and the frontier experiences a discrete jump whenever a new iPhone product is introduced, confirming the perception that the quality frontier is driven by the iPhone products. Also consistent with the common belief, we find that the median quality has risen over time. In fact, the median quality stays at a relatively constant distance behind the frontier. As for the quality frontiers of Apple and Samsung, Figure 1 shows that Samsung has narrowed the quality gap between its smartphone products and Apple's iPhones.

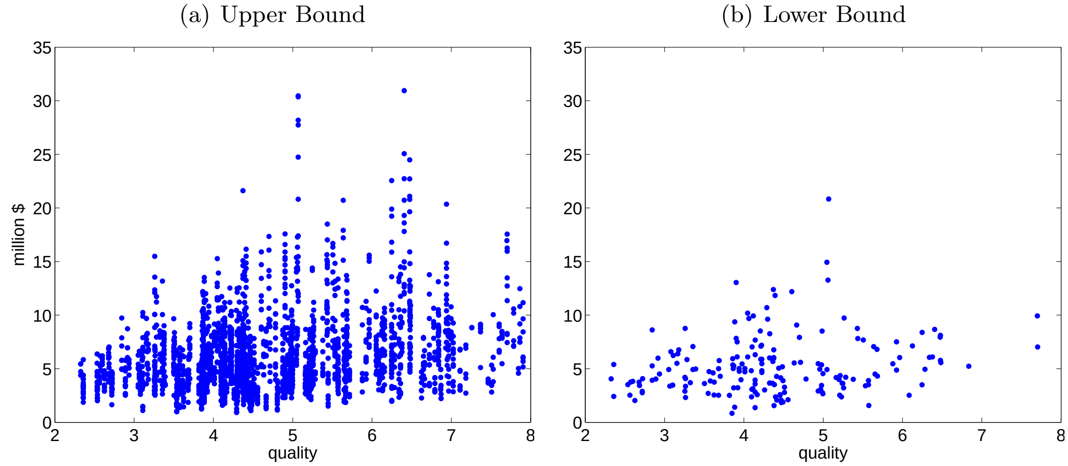
Figure 1: Smartphone Quality over Time



On the supply side, we find that marginal cost increases in product quality. Though not reported in Table 4, the estimated carrier/year fixed effects indicate that marginal cost is decreasing over time. It should be noted that the estimated marginal cost is in fact a smartphone firm's marginal cost subtracted by a carrier's per-consumer service profit. The estimated time trend therefore accounts for changes in the marginal cost of smartphones as well as changes in the service profit of a carrier.

Based on the estimates of the demand and the marginal cost functions, we obtain an upper bound of the fixed cost for product-month combinations in the data. The average upper bound, averaged across all such product-month combinations, is 6.16 million dollars. Figure 2(a) plots these upper bounds. The horizontal axis is the quality of a product, the same quality index in Figure 1. The vertical axis of Figure 2(a) shows the upper bound of the fixed cost. This figure suggests that the upper bound of the fixed cost is positively correlated with the quality of a product. As for the lower bound, as mentioned, we could obtain a lower bound of F_{jt} for any $j \notin \mathcal{J}_t$. In Figure 2(b), we plot the lower bounds for discontinued products. The average lower bound is 5.24 million dollars.

Figure 2: Bounds of Fixed Costs (Million $)



5 Counterfactual Simulations

In this section, we conduct counterfactual simulations to address the two research questions of the paper. In all counterfactual simulations, we keep the set of flagship products as fixed and only allow the number and the composition of non-flagship products to be adjusted. As mentioned, we do so to separate the issue of product variety from the issue of innovation. Therefore, for simplicity of exposition, a product in this section refers to a non-flagship product whenever it is not explicitly specified.

5.1 Are there too few or too many products?

There are two reasons why product offerings in an oligopoly market are inefficient. First, given the competitors' products, a firm will offer a product as long as the marginal profit from doing so is positive, but part of this marginal profit may come from business stealing. Since the firm does not take into account this potentially negative externality when making its decision on products, there might be too many products from a welfare point of view. Second, consumer surplus is not part of a firm's objective function. If consumer surplus increases when a product is added to the market, there might also be too few products. Because of the two potentially countervailing forces, whether there are too few or too many products is an empirical question.

To address this question, we first conduct counterfactual simulations where we remove products. Specifically, for March 2013, the last month of our data, we remove the lowest-quality product in the month, solve for the new pricing equilibrium, and then compute the corresponding consumer surplus and producer surplus. We repeat this counterfactual simulation for removing the median-quality product or removing the highest-quality product, and report the results in Table 7. Each column of the table corresponds to a simulation where a different product is removed. In the first three

rows of the table, we report changes in consumer surplus, carrier surplus (i.e., the sum of carriers' profits) and the sum of smartphone firms' variable profits. All three measures are expectations over the demand and the marginal cost shocks. In the last row, we report the upper bound of the removed product's fixed cost, which is the maximum possible saving in fixed costs.

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

Removed product	Lowest-quality	Median	Highest
Δ(consumer surplus)	-1.20	-3.60	-6.29
Δ(carrier surplus)	-0.92	-1.84	-4.94
Δ(smartphone producer variable profits)	-0.76	-1.45	-1.54
upper bound of savings in fixed costs	1.17	3.07	6.00

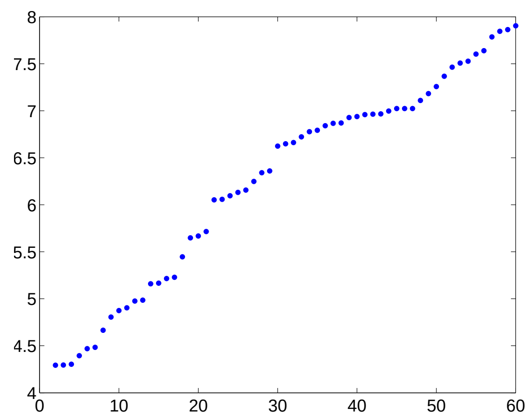
Across all three columns of Table 7, we can see that consumers are worse off when a product is removed. This is partially due to changes in prices after a product is a removed, but mainly because of the direct effect of removing a product. We can see this because when we hold prices of remaining products fixed, we find that changes in consumer surplus are (-1.17, -3.05, -5.96) million dollars across the three columns, which account for, respectively, 97%, 85% and 95% 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 the 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 can see that even considering the maximum possible saving in the fixed cost, removing the lowest-quality product in the month leads to a decrease in the total welfare.

Comparing the three columns, we can see that the changes in all welfare measures become larger as we move from removing the lowest-quality to the median-quality and then 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 60 products in the market, we find that the results in Table 7 hold in all 60 simulations. Specifically, Δ(consumer surplus), Δ(carrier surplus) and Δ(smartphone producer variable profits) are also always negative; the sum of them plus the upper bound of the removed product's fixed cost is always negative. These results indicate that removing any product in the market leads to a decrease in total welfare even 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 this exercise for removing any two products and find that the conclusion still holds.

In summary, the above results suggest that removing any one or two of the existing products in this market is welfare-decreasing. However, could adding a product lead to an increase in welfare? To answer this question, it is sufficient to find one product adding which increases total welfare. To this end, we consider a product that fills a gap in the quality spectrum. Specifically, we plot qualities of the products in March 2013 in Figure 3, find the largest gap in quality (i.e., the gap between 5.71 and 6.05) and add a product whose quality is at the midpoint of the gap (i.e., 5.88).

Figure 3: Quality of Products in March 2013



We consider four different simulations where this product is added to Samsung's, LG's, HTC's or Motorola's product portfolio. In all four simulations, we choose Sprint, the carrier with the least number of products, as its carrier. The simulation results are presented in Table 8, each column of which represents a different simulation.

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

	HTC	LG	Motorola	Samsung
Δ(consumer surplus)	2.45	2.43	2.49	2.76
Δ(carrier surplus)	1.34	1.34	1.36	1.58
Δ(smartphone producer variable profits)	1.10	1.11	1.09	1.70
lower bound of added fixed costs	2.14	2.13	2.16	2.63

Not surprisingly, consumers are better-off with the additional product in the market. Carriers also earn more profits. Smartphone firms' total variable profit increases. For the added product, we can obtain a lower bound on its fixed cost, which is reported in the last row of Table 8. The ratio of the sum of the first three rows of Table 8 to the lower bound is around 2.3 for all four simulations. This implies that as long as the fixed cost is not more than 2.3 times of its estimated lower bound, adding this product is welfare-improving. To put the number 2.3 in perspective, note that the average upper bound is about 1.2 times of the average lower bound we obtain in the estimation.

Overall, our simulation results from removing products and adding products suggest that there

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

5.2 How does competition affect product offerings?

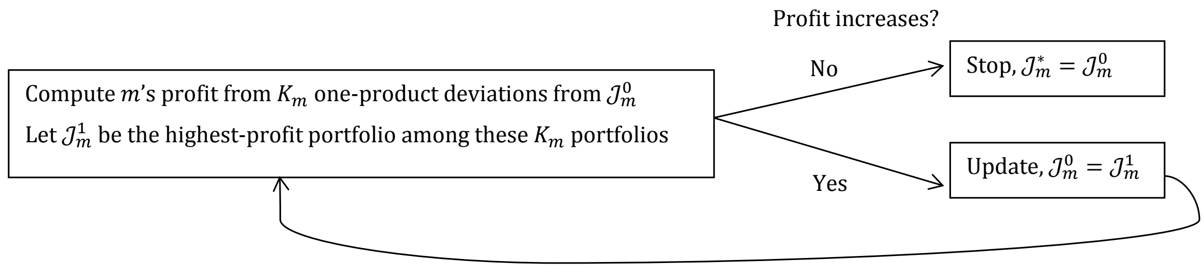
To study how competition affects product offerings, we simulate the effect of a hypothetical merger between Samsung and LG in March 2013, the second and the third largest smartphone firms in terms of sales in this month, following Apple. In Appendix B, we also show the effects of a Samsung-Motorola merger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

Computing the post-merger product-choice equilibrium can be challenging because the product-choice action space for a firm can be very large. A firm can choose to drop any set of products or add any number of products after the merger. To keep the problem tractable, we restrict the set of potential products for each firm in the merger simulations to be this firm's products in the data in either this month or last month, plus 8 additional potential products. These additional potential products are chosen to fill the gaps in the quality spectrum. As shown in the plot of the qualities of products in March 2013 (Figure 3), there are some gaps in the quality spectrum, for example, one between 5.71 and 6.05 and another between 6.35 and 6.62. We find the midpoints of these gaps (i.e., 5.88 and 6.49) and allow each firm to add a product whose quality is either 5.88 or 6.49. This product can be sold through any of the four carriers in the sample. Thus, there are 8 additional potential products for each firm to choose from.[12]

Even with this restricted set of potential products, the choice set for a firm can still be too large. This is because a smartphone firm chooses a product portfolio, which is a subset (of any size) of the potential products. In other words, the choice set of a firm is the power set of its potential products. For example, the merged Samsung-LG has 44 potential products, and thus the choice set consists of 2^{44} ($\approx 1.8 \times 10^{13}$) product portfolios. Moreover, in computing the profit of each of these product portfolios, we need to compute the corresponding pricing equilibrium, making the computational burden prohibitively high. To deal with this problem, we use a heuristic algorithm to compute a firm's optimal product portfolio given competitors' product portfolios. This algorithm is then

[12] Since we do not have an estimate on the brand effect of the merged Samsung-LG, in the merger simulation, we assign the Samsung brand effect to products that are originally offered by Samsung before the merger, and LG brand effect to those that are originally offered by LG. To be consistent, we allow 16 additional potential products for the merged Samsung-LG, 8 of which carry the Samsung brand effect and the other 8 of which carry the LG brand effect. In Appendix C, we repeat the merger simulation by assuming the post-merger Samsung-LG brand effect is the average of the pre-merger Samsung brand effect and LG brand effect. The results are robust.

Figure 4: Algorithm for Computing the Best-Response Product Portfolio



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 4. Specifically, we start with a portfolio $\mathcal{J}_m^0$ and compute firm m's profit from each one of the following deviations from $\mathcal{J}_m^0$: a product in $\mathcal{J}_m^0$ is removed or a potential product not in $\mathcal{J}_m^0$ is added. There are K_m such deviations, where K_m is the number of potential products for m. Each of such deviations differs from $\mathcal{J}_m^0$ in only one product. Let $\mathcal{J}_m^1$ be the highest-profit deviating product portfolio. If firm m's profit corresponding to $\mathcal{J}_m^1$ is smaller than that corresponding to $\mathcal{J}_m^0$, this procedure stops and returns $\mathcal{J}_m^0$ as the best response. Otherwise, we compute m's profit from any one-product deviation from $\mathcal{J}_m^1$ by either adding a potential product to or dropping a product from $\mathcal{J}_m^1$. We continue this process until firm m's profit does not increase any more. In sum, this heuristic algorithm essentially simplifies a problem growing exponentially in the number of potential products K_m into one growing linearly in K_m.

In this algorithm, even though we impose the 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 the number and the composition. This is because before convergence, each step of the algorithm leads to a one-product deviation and the profit strictly increases. Therefore, as long as the algorithm does not converge in one step, it yields a product portfolio that deviates from the starting product portfolio by more than one products. The composition can also change as the algorithm can drop one product in one step and add another in a later step.

In Appendix D, we conduct Monte Carlo simulations to evaluate the performance of the algorithm. The results from Monte Carlo simulations suggest that this algorithm works well, at least for relatively small problems where we can solve for the true optimal product portfolio without using the heuristic algorithm. Given that the key restriction of the heuristic algorithm is the one-product deviation in each step, we also check and confirm that, at the equilibrium found by the heuristic algorithm, no firm has any two-product profitable deviation.

As mentioned, we embed this heuristic algorithm in a best-response iteration, where firms take turns to update its product portfolio to its best-response product portfolio. The iteration converges

when no firm has an incentive to deviate any more. We use two movement orders for the best-response iteration: we loop over firms according to their monthly sales in March 2013, either in an ascending order or a descending order. It turns out that the two best-response iterations yield the same equilibrium in our merger simulations.

As for fixed costs, we draw the fixed cost for each potential product from a range consistent with the bounds obtained in the estimation and report the average merger effects, averaged over different sets of fixed-cost draws. Specifically, for each product in the data (i.e., j such that $j \in \mathcal{J}_t$), we have obtained an upper bound of its fixed cost (denoted by $\bar{F}_{jt}$). For such a product, we randomly draw five fixed-cost values from the range $\left[0.5\bar{F}_{jt}, \bar{F}_{jt}\right]$. Similarly, for each potential product not in the data, we obtain a lower bound of its fixed cost $\underline{F}_{jt}$, and draw five fixed-cost values from $\left[\underline{F}_{jt}, 5\underline{F}_{jt}\right]$. 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 $\underline{F} = 5.24$ 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. We show in Appendix B that the merger simulation results are robust to these two alternative fixed-cost ranges.

To capture the effect of merger on product variety, we 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 qualities of the n products sorted in an ascending order. This measure resembles the CES utility function, and has two desirable properties. First, given the range of quality (i.e., $q^{(n)} - q^{(1)}$), this measure is maximized when the products in between are equidistantly distributed. 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 $\left(q^{(n)} - q^{(1)}\right)$.

Table 9 presents the merger simulation results. It shows that after the merger, the number of products decreases by 2.40 on average. As we can see from the decomposition of this change into that for the merged firm and that for the non-merging firms (Rows (2) and (3)), this decrease is mainly driven by the merged firm dropping products: the average change for the merged firm is -3.20 and that for the non-merging firms is 0.80. The merged firm drops products across the quality spectrum with a concentration on the middle range. The average number of products dropped from each quality quartile (i.e., below the pre-merger 25% quality quantile, [25% quantile, 50% quantile), [50% quantile, 75% quantile), or above the 75% quantile) is, respectively, 0.6, 1.4, 1 and 0.2. Overall, the product variety measure decreases by 18.18 (from 338.32). 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 6.45. The pre-merger product variety measure (338.32) is as if there are 53.40 equidistantly distributed products (338.32/6.45 + 1). Similarly, the post-merger product variety measure (320.14) is as if there are 50.61 equidistantly distributed products. Therefore, a change of -18.18 in the product variety measure is equivalent to a decrease in the number of "as if" equidistantly distributed products by about 2.79.

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

	Variable	Pre-merger	Post-merger	Change
(1)	Number of non-flagship products	60.00	57.60	-2.40
(2)	Merged firm	27.00	23.80	-3.20
(3)	Non-merging firms	33.00	33.80	0.80
(4)	Variety	338.32	320.14	-18.18
(5)	Sales-weighted avg quality	8.29	8.31	0.02
(6)	Merged firm	7.29	7.32	0.02
(7)	Non-merging firms	6.18	6.18	0.001
(8)	Sales-weighted avg price ($)	128.17	129.33	1.16
(9)	Merged firm	193.07	202.82	9.75
(10)	Non-merging firms	100.78	101.14	0.36
(11)	Total sales	7,012,791	6,913,513	-99,278
(12)	Merged firm	2,081,704	1,916,802	-164,902
(13)	Non-merging firms	4,931,086	4,996,710	65,624
(14)	Consumer surplus (million $)	1633.75	1603.19	-30.57
(15)	Carrier profit (million $)	1282.04	1263.04	-19.01
(16)	Smartphone firm profit (million $)	1110.77	1124.59	13.82
(17)	Merged firm	285.79	287.69	1.90
(18)	Non-merging firms	824.98	836.90	11.92

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

In the end, while the sales-weighted average quality in the market barely changes, the sales-weighted average retail price increases by 1.16 dollars. This is largely due to increases in the prices of the merged firm's products. Row (9) shows that the sales-weighted average retail price of the merged firm's products increases by about 9.75 dollars. Overall, sales for the merged firm decreases and that for the non-merging firms increases, with a net change of -99,278 units. The decrease in product offerings and the increase in prices lead to a reduction in consumer surplus by around 31 million dollars. Carriers are also worse off. The total smartphone profit increases by around 13.82 million dollars, among them 1.90 million dollars are attributed to the increase in the merged firm's profit and the remaining 11.92 million dollars are due to changes in non-merging firms' profits with an average increase of 1.08 million dollars per non-merging firm. Despite the increase in smartphone producer surplus, the overall welfare decreases by around 35.76 million dollars.

In summary, results from this counterfactual simulation show that a reduction in competition leads to a decrease in the number of products across the quality spectrum. Such a decrease in product variety is accompanied by an increase in prices, and leads to a decline in consumer surplus and carrier surplus, and eventually a reduction in the overall welfare despite an increase in smartphone producer surplus. These findings hold for other mergers as well (see Appendix B for the Samsung-Motorola merger and the LG-Motorola merger). Recall that in Section 5.1, we find that there are too few products in the market from a welfare point of view. In this section, we find that

a merger further reduces product offerings. The combination of these results suggests that merger policies should be stricter when we take into account the effect of merger on product offerings.

This conclusion is also consistent with a merger simulation where we keep the set of products fixed and only allow firms to adjust prices after the merger. In such a merger simulation, we find that the changes in all welfare measures are smaller (in the absolute value). The changes in consumer surplus, carrier profit and smartphone firm profit are, respectively, -19.18, -11.44 and 6.68 million dollars. In contrast, they are -30.57, -19.01 and 13.82 million dollars when post-merger adjustments in both product offerings and prices are allowed. The decrease in total surplus is also smaller, again suggesting that the merger policy should be stricter considering firms' endogenous product choice.

6 Robustness

One concern with our discrete choice model is that the assumption of independent idiosyncratic shocks may lead to an overestimation of the consumer surplus gain when a product is added. To address this concern, we conduct two robustness analyses where we add more random coefficients in order to allow more correlation among the utilities that a consumer gets from different products. For both robustness analyses, we re-estimate the model and also repeat the counterfactual simulations using the new model and the new estimates.

In the first robustness analysis, we add a random coefficient for the Apple dummy variable. We allow this random coefficient to be correlated with the quality random coefficient and also estimate the correlation. The estimation results are reported in Table 10(a). The estimation results indicate that the standard deviation of the Apple-dummy random coefficient is 2.821, and this random coefficient is highly correlated with the quality random coefficient. The estimated correlation is 0.991. Unfortunately, both estimates are statistically insignificant. For parameters common in both models, the estimates and the statistical significance levels are largely robust. More importantly, the results from the counterfactual simulations, which allow us to address our research questions, are also robust. We report these simulation results in Tables 10(b)-(d). From these tables, we can see that all the findings discussed before still hold. For example, we still find that removing a product reduces total surplus even considering the maximum possible saving in the fixed cost; adding a product will increase total surplus as long as the fixed cost is not much higher than its lower bound; and a merger leads to a reduction in product offerings and eventually a decrease in total welfare.

In the second robustness analysis, we allow a random coefficient for each carrier dummy variable. The estimation results in Table 11(a) show that the standard deviations of the AT&T dummy and the Sprint dummy are small and statistically insignificant. Those of the T-Mobile and the Verizon dummies are 3.67 and 2.09, about 40% and 20% of their corresponding means. The estimates

Table 10: Robustness Analysis: Allowing an Apple Random Coefficient

(a) Estimation Results

	Parameter	Std. Error
Demand		
Quality coefficient		
Battery talk time (hours)	0.043***	0.017
Camera resolution (megapixel)	0.102***	0.048
Chipset generation 2	0.453***	0.141
Chipset generation 3	0.752***	0.188
Chipset generation 4	1.231***	0.280
Chipset generation 5	1.930***	0.410
Screen size (inch)	1	
Weight (gram)	-0.002	0.002
Covariance of random coefficients		
Std. Dev., quality	0.185*	0.110
Std. Dev., Apple	2.821	2.320
Correlation	0.991	1.790
Quality	0.838***	0.202
Price	-0.006***	0.002
Apple	-0.179	2.187
BlackBerry	1.124***	0.131
Samsung	0.320***	0.068
Flagship?	0.670***	0.068
Carrier/year and quarter dummies	Yes	
Marginal Cost ($)		
Exp(quality/10)	541.119***	2.507
Apple	-269.435***	0.143
BlackBerry	103.951***	0.444
Samsung	-19.399***	0.134
Carrier/year dummies	Yes	

* indicates 90% 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)	-1.40	-4.16	-7.19
Δ(carrier surplus)	-1.16	-2.64	-4.39
Δ(smartphone producer variable profits)	-0.93	-1.75	-2.22
upper bound of savings in fixed costs	1.39	3.57	5.81

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

	HTC	LG	Motorola	Samsung
Δ(consumer surplus)	2.77	2.76	2.80	3.25
Δ(carrier surplus)	1.86	1.86	1.87	2.23
Δ(smartphone producer variable profits)	1.31	1.32	1.30	1.97
lower bound of added fixed costs	2.45	2.45	2.46	3.07

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

Variable	Pre-merger	Post-merger	Change
Number of non-flagship products	60.00	57.60	-2.40
Variety	311.15	291.39	-19.77
Sales-weighted avg quality	6.81	6.80	-0.01
Sales-weighted avg price ($)	128.48	130.07	1.59
Total sales	7,046,884	6,944,395	-102,489
Consumer surplus (million $)	2365.82	2335.23	-30.60
Carrier profit (million $)	1581.08	1559.14	-21.94
Smartphone firm profit (million $)	1864.35	1877.75	13.40

Table 11: Robustness Analysis: Allowing Carrier Random Coefficients

(a) Estimation Results

	Parameter	Std. Error
Demand		
Quality coefficient		
Battery talk time (hours)	0.053***	0.017
Camera resolution (megapixel)	0.086***	0.037
Chipset generation 2	0.465***	0.126
Chipset generation 3	0.738***	0.174
Chipset generation 4	1.130***	0.228
Chipset generation 5	1.769***	0.315
Screen size (inch)	1	
Weight (gram)	-0.001	0.001
Std. Dev. of random coefficients		
Quality	0.297***	0.097
AT&T	0	19.764
Sprint	0.632	11.260
T-Mobile	3.665***	1.541
Verizon	2.093**	1.131
Quality	0.790***	0.153
Price	-0.007***	0.002
Apple	2.700***	0.135
BlackBerry	1.210***	0.123
Samsung	0.316***	0.071
Flagship?	0.676***	0.080
Carrier/year and quarter dummies	Yes	
Marginal Cost ($)		
Exp(quality/10)	459.980***	2.186
Apple	-39.862***	0.109
BlackBerry	84.404***	0.387
Samsung	-27.922***	0.119
Carrier/year dummies	Yes	

** 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)	-0.92	-4.73	-6.19
Δ(carrier surplus)	-1.05	-2.60	-6.23
Δ(smartphone producer variable profits)	-0.23	-1.65	-0.37
upper bound of savings in fixed costs	0.93	4.09	5.98

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

	HTC	LG	Motorola	Samsung
Δ(consumer surplus)	2.28	2.23	2.35	2.69
Δ(carrier surplus)	1.29	1.27	1.32	1.58
Δ(smartphone producer variable profits)	1.02	1.04	1.00	1.59
lower bound of added fixed costs	1.97	1.95	2.00	2.50

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

Variable	Pre-merger	Post-merger	Change
Number of non-flagship products	60.00	57.40	-2.60
Variety	335.74	312.01	-23.72
Sales-weighted avg quality	8.45	8.46	0.02
Sales-weighted avg price ($)	133.55	134.73	1.17
Total sales	6,610,352	6,525,181	-85,171
Consumer surplus (million $)	1654.24	1624.52	-29.72
Carrier profit (million $)	1540.14	1513.54	-26.60
Smartphone firm profit (million $)	1088.90	1107.62	18.72

of parameters common to two models are robust. The counterfactual simulation results are also robust (see Tables 11(b)-(d)).

In sum, through these analyses, we have shown that our results are robust to certain variations to the demand side of the model. In Appendix E, we also investigate the robustness with respect to the supply side of the model. Specifically, we investigate the robustness of our results to deviations from the simple linear pricing model.

7 Conclusion

In this paper, we study how efficient product proliferation as an outcome of firms' competition in product space is and, in turn, how competition affects proliferation in the U.S. smartphone market. To this end, we develop and estimate a model for the demand and supply of smartphones. We conduct counterfactual simulations where we add or remove products to answer the question of whether there are too few or too many products in the market. We also use merger simulations to study the effects of competition on product offerings, prices and welfare. We find that there are too few products in the market, and a reduction in competition decreases product offerings, lowers product variety and reduces total welfare. These results suggest that merger policies should be stricter when we take into account the merger effect on product choice.

We conclude the paper by highlighting a few caveats of the paper. First, similar to many papers in the endogenous product choice literature,[13] this paper sets up a static model to describe consumer demand and firm behavior. On the supply side, this modeling choice is somewhat justifiable because we focus on firms' decisions on non-flagship products, which presumably do not involve a large sunk cost such as the R&D cost. However, due to frictions such as switching costs, 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. Note that in a reduced-form way, our carrier/year fixed effects in the utility function capture the average switching cost. 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. That said, we do keep this fixed effect constant in the counterfactual simulations and therefore do not discuss industry dynamics.

Second, our model does not explain why a product is sold through a specific carrier. This means that we do discuss the effect of competition on the carrier choice for each product, which may affect the pricing equilibrium, and thus also affect smartphone firms' product offerings. The carrier choice is particularly important when switching costs are prominent. Unfortunately, without individual-level data which may help us to reliably identify the switching cost and without information on

[13] For example, Seim (2006), Fan (2013), Eizenberg (2014), Crawford, Shcherbakov and Shum (2015).

the contracts between a carrier and a smartphone firm, it is difficult for us to discuss the carrier choice. We therefore leave this for future research.

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Appendices

A List of Flagship Smartphones

Flagship Products (2009/01 - 2013/03)

Brand	Model	Brand	Model
Apple	all iPhones	LG	Optimus One
BlackBerry	88XX		Optimus 2X
	Curve		Optimus G
	Storm	Motorola	Droid
	Bold		Droid X
	Tour		Atrix 4G
	Torch		Droid Bionic
	Bold Touch		Droid Razr
	BlackBerry 10		Droid Razr Maxx
HTC	G1		Droid Razr M
	myTouch 3G	Nokia	Lumia 900
	Hero		Lumia 920
	myTouch 4G	Samsung	Galaxy S
	Desire HD		Galaxy S II
	Sensation 4G		Galaxy S III
	One X		Galaxy Note II

B Additional Merger Simulations

In Section 5, we have shown the simulation result for a merger between Samsung and LG in March 2013, the second and the third largest firms in terms of sales in that month. In this section, we conduct two additional merger simulations: the Samsung-Motorola merger (a merger between the second-largest and the fourth-largest firms) and the LG-Motorola merger (a merger between the third-largest and the fourth-largest firms). The simulation results are presented in Table B.1. 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, but the qualitative findings are robust. Specifically, we find that all three mergers lead to a decrease in product variety. In terms of welfare measures, all three mergers result in a decrease in both consumer surplus and carrier surplus, but an increase in smartphone producer surplus. The overall welfare effect is always negative.

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

	Variable	Pre-merger	Post-merger	Change
	The Samsung-Motorola Merger			
(1)	Number of non-flagship products	60.00	58.00	-2.00
(2)	Merged firm	21.00	18.80	-2.20
(3)	Non-merging firms	39.00	39.20	0.20
(4)	Variety	338.32	332.05	-6.28
(5)	Sales-weighted avg quality	8.29	8.30	0.02
(6)	Merged firm	7.32	7.33	0.01
(7)	Non-merging firms	6.18	6.18	0.001
(8)	Sales-weighted avg price ($)	128.17	128.67	0.49
(9)	Merged firm	198.38	205.17	6.79
(10)	Non-merging firms	99.42	99.69	0.26
(11)	Total sales	7,012,791	6,930,131	-82,659
(12)	Merged firm	2,037,476	1,903,753	-133,723
(13)	Non-merging firms	4,975,315	5,026,378	51,063
(14)	Consumer surplus (million $)	1633.75	1608.11	-25.64
(15)	Carrier profit (million $)	1282.04	1263.22	-18.83
(16)	Smartphone firm profit (million $)	1110.77	1124.11	13.34
(17)	Merged firm	291.77	293.73	1.96
(18)	Non-merging firms	819.00	830.38	11.38
	The LG-Motorola Merger			
(1)	Number of non-flagship products	60.00	59.40	-0.60
(2)	Merged firm	16.00	15.40	-0.60
(3)	Non-merging firms	44.00	44.00	0.00
(4)	Variety	338.32	336.49	-1.84
(5)	Sales-weighted avg quality	8.29	8.29	0.01
(6)	Merged firm	7.05	7.03	-0.01
(7)	Non-merging firms	6.44	6.44	2.17E-04
(8)	Sales-weighted avg price ($)	128.17	128.27	0.09
(9)	Merged firm	173.69	176.43	2.74
(10)	Non-merging firms	122.74	122.83	0.09
(11)	Total sales	7,012,791	6,989,440	-23,350
(12)	Merged firm	748,122	708,909	-39,214
(13)	Non-merging firms	6,264,668	6,280,532	15,864
(14)	Consumer surplus (million $)	1633.75	1626.57	-7.19
(15)	Carrier profit (million $)	1282.04	1276.58	-5.46
(16)	Smartphone firm profit (million $)	1110.77	1115.14	4.37
(17)	Merged firm	62.98	63.19	0.21
(18)	Non-merging firms	1047.78	1051.95	4.16

C Merger Simulations with Different Specifications

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

As mentioned in Footnote 12, for the merger simulation in Section 5, we assign the Samsung brand effect to products that are originally offered by Samsung before the merger, and LG brand effect to those that are 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 LG brand effect. Results in C.2 show that the simulation results in Section 5 are robust to this change.

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

	Variable	Pre-merger	Post-merger	Change
(1)	Number of non-flagship products	60.00	57.60	-2.40
(2)	Merged firm	16.00	13.60	-2.40
(3)	Non-merging firms	44.00	44.00	0.00
(4)	Variety	338.32	320.14	-18.18
(5)	Sales-weighted avg quality	8.29	8.31	0.02
(6)	Merged firm	7.05	7.04	0.00
(7)	Non-merging firms	6.44	6.44	-0.005
(8)	Sales-weighted avg price ($)	128.17	129.33	1.16
(9)	Merged firm	173.69	185.99	12.31
(10)	Non-merging firms	122.74	123.66	0.93
(11)	Total sales	7,012,791	6,913,513	-99,278
(12)	Merged firm	748,122	629,482	-118,641
(13)	Non-merging firms	6,264,668	6,284,031	19,363
(14)	Consumer surplus (million $)	1633.75	1603.19	-30.57
(15)	Carrier profit (million $)	1282.04	1263.04	-19.01
(16)	Smartphone firm profit (million $)	1110.77	1124.59	13.82
(17)	Merged firm	62.98	35.52	-27.47
(18)	Non-merging firms	1047.78	1089.07	41.29

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 $\left[\underline{F}_{jt}, 5\underline{F}_{jt}\right]$ for a potential product not in the data. In this section, we consider two different ranges:

(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 $\underline{F} = 5.24$ 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, analogously, $L_l(q_{jt})$ is analogously defined using the lower bounds reported.

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

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

	Variable	Pre-merger	Post-merger	Change
	Alternative Fixed-cost Range (1)			
(1)	Number of non-flagship products	60.00	57.40	-2.60
(2)	Merged firm	27.00	21.20	-5.80
(3)	Non-merging firms	33.00	36.20	3.20
(4)	Variety	338.32	321.88	-16.44
(5)	Sales-weighted avg quality	8.29	8.30	0.02
(6)	Merged firm	7.29	7.33	0.04
(7)	Non-merging firms	6.18	6.18	0.003
(8)	Sales-weighted avg price ($)	128.17	127.61	-0.56
(9)	Merged firm	193.07	202.02	8.95
(10)	Non-merging firms	100.78	100.75	-0.03
(11)	Total sales	7,012,791	6,905,994	-107,000
(12)	Merged firm	2,081,704	1,832,424	-249,000
(13)	Non-merging firms	4,931,086	5,073,570	142,000
(14)	Consumer surplus (million $)	1633.75	1600.02	-33.70
(15)	Carrier profit (million $)	1282.04	1261.29	-20.80
(16)	Smartphone firm profit (million $)	1070.62	1086.40	15.80
(17)	Merged firm	267.24	269.22	1.99
(18)	Non-merging firms	803.39	817.18	13.80
	Alternative Fixed-cost Range (2)			
(1)	Number of non-flagship products	60.00	57.60	-2.40
(2)	Merged firm	27.00	21.80	-5.20
(3)	Non-merging firms	33.00	35.80	2.80
(4)	Variety	338.32	317.76	-20.56
(5)	Sales-weighted avg quality	8.29	8.30	0.02
(6)	Merged firm	7.29	7.33	0.04
(7)	Non-merging firms	6.18	6.18	0.002
(8)	Sales-weighted avg price ($)	128.17	128.11	-0.07
(9)	Merged firm	193.07	202.59	9.52
(10)	Non-merging firms	100.78	100.85	0.07
(11)	Total sales	7,012,791	6,907,758	-105,032
(12)	Merged firm	2,081,704	1,850,750	-230,954
(13)	Non-merging firms	4,931,086	5,057,008	125,922
(14)	Consumer surplus (million $)	1633.75	1600.80	-32.95
(15)	Carrier profit (million $)	1282.04	1262.11	-19.93
(16)	Smartphone firm profit (million $)	1075.53	1090.30	14.76
(17)	Merged firm	269.42	271.17	1.74
(18)	Non-merging firms	806.11	819.13	13.02

D Monte Carlo Test of the Heuristic Algorithm

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

These Monte Carlo simulations are constructed as follows. We first randomly draw K products from Samsung's non-flagship products in March 2013. For each one of these K products, we compute the variable profit if this product is 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 these K variable profits.[14] Given these fixed-cost draws, we compute the firm's profit (variable profit less the fixed cost) corresponding to each of the 2^K possible product portfolios and 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., (# 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 D.1, for each of the eight Monte Carlo studies where K varies between 3 and 10, we plot the maximum of this failure rate across all 2^K starting points. The figure shows that as the number of potential products (K) increases, the maximum failure rate increases.[15] 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.

E Additional Robustness Analyses

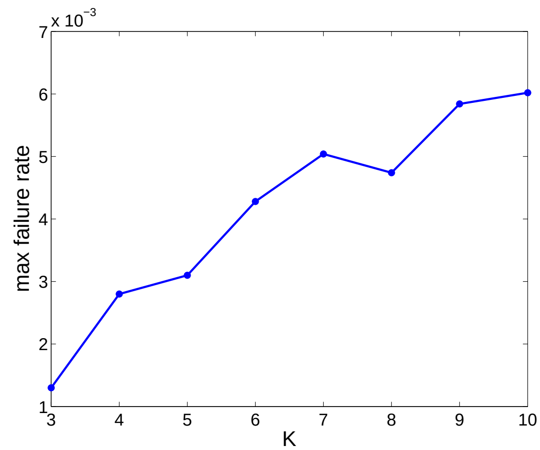
We have shown in Section 6 that our results are robust to various changes to the demand side of the model. In this section, we examine whether our results are also robust to assumptions on the supply side of the model. Note that in the baseline model, the supply side is a simple linear pricing model, which implies that there exists double marginalization as follows:

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

[14]We do not use the bounds we 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 data. As a result, the change in variable profit from adding or removing a product in this exercise is larger than that in Section 4.2. If we were to use the bounds reported there, we would find, in this exercise, that it is always optimal to have all K products in the market.

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

Figure D.1: Failure Rate of the Heuristic Algorithm



where 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 smartphone firms' and/or carriers' pricing strategies deviate from the above simple 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:

$$\boldsymbol{p} = \left[(-\Gamma_c\Delta_c)^{-1}\,\boldsymbol{s}\right] \circ \Lambda_c + \left[(-\Gamma_m\Delta_m)^{-1}\,\boldsymbol{s}\right] \circ \Lambda_m + \tilde{\boldsymbol{mc}}, \tag{E.2}$$

where the operator $\circ$ represents the element-wise multiplicity.

Note that when Λ_c and Λ_m are both a constant-1 vector, equation (E.2) becomes the simple linear pricing equation (E.1). With a slight abuse of notation, we refer to this case as ($\Lambda_c = 1, \Lambda_m = 1$). In this section, we examine two "extreme" deviations as robustness analyses: when ($\Lambda_c = 0, \Lambda_m = 1$) and when ($\Lambda_c = 1, \Lambda_m = 0$). For both robustness analyses, we re-estimate the marginal cost parameters and the bounds on the fixed costs, and repeat the counterfactual simulations. In what follows, we suppress the subscript "t" for simplicity of exposition.

Note that in the case of ($\Lambda_c = 0, \Lambda_m = 1$), there may be a transfer from a smartphone firm to a carrier. Let T_m be the total transfer that a smartphone firm m pays, $T_{m,\setminus j}$ be the transfer when product j is removed from m's product portfolio, and $T_{m,\cup j}$ be the transfer when product j is added to m's product portfolio. Then, the two inequalities (11) and (12) in Section 3, which

capture the optimality conditions for m's product choice in the baseline model, become

$$E_{(\boldsymbol{\xi},\boldsymbol{\omega})}\pi_m(\boldsymbol{q},\boldsymbol{\xi},\boldsymbol{\omega})-F_j-T_m\geq E_{(\boldsymbol{\xi},\boldsymbol{\omega})}\pi_m(\boldsymbol{q}\backslash q_j,\boldsymbol{\xi}\backslash\xi_j,\boldsymbol{\omega}\backslash\omega_j)-T_{m,\backslash j}\text{ for any }j\in\mathcal{J}_m \tag{E.3}$$
$$E_{(\boldsymbol{\xi},\boldsymbol{\omega})}\pi_m(\boldsymbol{q},\boldsymbol{\xi},\boldsymbol{\omega})-T_m\geq E_{(\boldsymbol{\xi},\boldsymbol{\omega})}\pi_m(\boldsymbol{q}\cup q_j,\boldsymbol{\xi}\cup\xi_j,\boldsymbol{\omega}\cup\omega_j)-F_j-T_{m,\cup j}\text{ for any }j\notin\mathcal{J}_m.$$

The two inequalities in (E.3) imply that for any $j\in\mathcal{J}_m$,

$$\begin{aligned}F_j &\leq \left[E_{(\boldsymbol{\xi},\boldsymbol{\omega})}\pi_m(\boldsymbol{q},\boldsymbol{\xi},\boldsymbol{\omega})-E_{(\boldsymbol{\xi},\boldsymbol{\omega})}\pi_m(\boldsymbol{q}\backslash q_j,\boldsymbol{\xi}\backslash\xi_j,\boldsymbol{\omega}\backslash\omega_j)\right]-\left[T_m-T_{m,\backslash j}\right] \\ &\triangleq \Delta\pi_{m,\backslash j}-\left[T_m-T_{m,\backslash j}\right]\triangleq\bar{F}_j,\end{aligned} \tag{E.4}$$

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

$$\begin{aligned}F_j &\geq \left[E_{(\boldsymbol{\xi},\boldsymbol{\omega})}\pi_m(\boldsymbol{q}\cup q_j,\boldsymbol{\xi}\cup\xi_j,\boldsymbol{\omega}\cup\omega_j)-E_{(\boldsymbol{\xi},\boldsymbol{\omega})}\pi_m(\boldsymbol{q},\boldsymbol{\xi},\boldsymbol{\omega})\right]-\left[T_{m,\cup j}-T_m\right] \\ &\triangleq \Delta\pi_{m,\cup j}-\left[T_m-T_{m,\cup j}\right]\triangleq\underline{F}_j.\end{aligned} \tag{E.5}$$

Under the assumption that the total transfer that a smartphone pays at least weakly increases with the number of its products, i.e., $T_m-T_{m,\backslash j}\geq 0$ and $T_{m,\cup j}-T_m\geq 0$, we have $\bar{F}_j\leq\Delta\pi_{m,\backslash j}$ and $\underline{F}_j\leq\Delta\pi_{m,\cup j}$. In Table E.4 where we present the simulation results where a product is removed or added, we report $\Delta\pi_{m,\backslash j}$ as the upper bound of the saving in fixed costs, and $\Delta\pi_{m,\cup j}$ as the lower bound. In doing so, we overestimate both bounds. From Table E.4, we can see that even with such an overestimation, our results are robust: removing a product leads to a decrease in the total welfare even considering the (over-estimated) maximum possible saving in the fixed cost; and 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.

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

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

Removed product	Lowest-quality	Median	Highest
Δ(consumer surplus)	-1.09	-3.42	-6.86
Δ(total producer surplus net of fixed costs)[a]	-0.64	-1.15	-2.19
$\Delta\pi_{m,\backslash j}$	1.03	3.00	6.00

[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)	2.39	2.40	2.39	2.69
Δ(total producer surplus net of fixed costs)	1.07	1.07	1.07	1.73
$\Delta\pi_{m,\cup j}$	2.18	2.19	2.18	2.69

Similarly, in the case of $(\Lambda_c=1,\Lambda_m=0)$, there is a transfer from a carrier to a smartphone.

Let T_m be the total transfer that a smartphone firm m receives, and $T_{m,\backslash j}$ 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

$$T_m - F_j \geq T_{m,\backslash j} \iff F_j \leq T_m - T_{m,\backslash j} \text{ for any } j \in \mathcal{J}_m \tag{E.6}$$

$$T_m \geq T_{m,\cup j} - F_j \iff F_j \geq T_{m,\cup j} - T_m \text{ for any } j \notin \mathcal{J}_m. \tag{E.7}$$

In Table E.5, which presents the simulation results in this robustness analysis, we report the changes in the (pre-transfer) profit of j's carrier as the bounds, i.e., $\Delta\pi_{c,\backslash j} = E_{(\boldsymbol{\xi},\boldsymbol{\omega})}\pi_c(\boldsymbol{q},\boldsymbol{\xi},\boldsymbol{\omega}) - E_{(\boldsymbol{\xi},\boldsymbol{\omega})}\pi_c(\boldsymbol{q}\backslash q_j,\boldsymbol{\xi}\backslash\xi_j,\boldsymbol{\omega}\backslash\omega_j)$ or $\Delta\pi_{c,\cup j} = E_{(\boldsymbol{\xi},\boldsymbol{\omega})}\pi_c(\boldsymbol{q}\cup q_j,\boldsymbol{\xi}\cup\xi_j,\boldsymbol{\omega}\cup\omega_j) - E_{(\boldsymbol{\xi},\boldsymbol{\omega})}\pi_c(\boldsymbol{q},\boldsymbol{\xi},\boldsymbol{\omega})$. Under the assumption that when a product is added, the increase in the amount of transfer that the smartphone firm receives is not larger than the increase in the carrier's (pre-transfer) profit (i.e., $T_m - T_{m,\backslash j} \leq \Delta\pi_{c,\backslash j}$ and $T_{m,\cup j} - T_m \leq \Delta\pi_{c,\cup j}$), the bounds of the fixed cost reported in Table E.5 are again over-estimated. Therefore, from Table E.5, we can draw a similar robustness conclusion as in the case of $(\Lambda_c = 0, \Lambda_m = 1)$. In sum, our results on welfare changes when a product is added or removed are robust to changes to the supply side of the model, specifically, to deviations to a simple linear pricing model.[16]

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

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

Removed product	Lowest-quality	Median	Highest
Δ(consumer surplus)	-0.87	-3.64	-5.03
Δ(total producer surplus net of fixed costs)	-0.80	-1.53	-3.96
$\Delta\pi_{c,\backslash j}$	1.14	3.68	7.47

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

	HTC	LG	Motorola	Samsung
Δ(consumer surplus)	2.21	2.21	2.21	2.76
Δ(total producer surplus net of fixed costs)	1.13	1.13	1.13	1.49
$\Delta\pi_{c,\cup j}$	2.18	2.18	2.18	2.50

[16] We do not conduct robustness analyses regarding the merger simulations because doing so requires us to make assumptions on how a merger affects the transfers between smartphone firms and carriers.