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

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Abstract

This paper studies (1) whether, from a welfare point of view, oligopolistic competition leads to too few or too many products in a market, and (2) how a change in competition affects the number and the composition of product offerings. We address these two questions in the context of the U.S. smartphone market. Our findings show that this market contains too few products and that a reduction in competition decreases both the number and variety of products. These results suggest that product choice adjustment may exacerbate the welfare effect of a merger.

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

1 Introduction

In many markets such as the printer market, the CPU market and the smartphone market, firms typically offer multiple products across a wide spectrum of quality. In these markets, product proliferation is an outcome of firms' oligopolistic competition in product space. Does such competition result in too few or too many products from a welfare point of view? How does a change in the level of competition affect the number and composition of product offerings? In this paper, we study these two questions in the context of the U.S. smartphone industry.

For the first question, in theory, it is possible that oligopolistic competition results in either too few or too many products. On the one hand, because firms do not take into account the business

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stealing externality, there may be too many products. On the other hand, because firms do not internalize consumer surplus, there may also be too few products. These two effects, which work in opposite directions, are highlighted in Spence (1976) and Mankiw and Whinston (1986) in the context of a single-product oligopoly. In a multi-product oligopoly, however, there exists another factor influencing the equilibrium product offerings: firms' incentives to avoid cannibalization of their own products, which may drive the equilibrium towards too few products.[1] Overall, because of these factors, whether competition leads to too few or too many products in the market is an empirical question.

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

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

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

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

[1] To understand this point, note that there are two sets of business stealing externalities: the externality of a product on the profit of its opponents' products and the externality of a product on the profit of own (other) products. While a social planner takes into account both sets, firms consider neither in a single-product oligopoly market (where each product is produced by a different firm). In a multi-product oligopoly market, firms take into account the second set of externalities but not the first set. Therefore, compared to a single-product oligopoly market, the equilibrium outcome is more likely to be such that there are too few products.

with substantial quality and price variation.

In order to address our research questions, we develop a structural model of consumer demand and firms' product and pricing decisions, and estimate the model using data from the Investment Technology Group (ITG) Market Research. This data set provides information on all smartphone products in the U.S. market between January 2009 and March 2013. For every month during this period, we observe both the price and the quantity of each smartphone sold through each of the four national carriers in the U.S. (AT&T, T-Mobile, Sprint, and Verizon). In addition, we observe key specifications of each product, such as battery talk time and camera resolution.

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

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

Based on the estimated demand, marginal cost and fixed cost bounds, we conduct counterfactual simulations to address our research questions. To answer the question of whether there are too few or too many products in the market, we conduct two sets of counterfactual simulations for March 2013, the last month in our sample period. In one set of counterfactual simulations, we remove products, while in the other set, we add products. Our results show that removing a product decreases total surplus, even considering the maximum saving in the fixed cost. These results are robust no matter which product or which two products we remove. In the second set of simulations, we add a product that fills a gap in the quality spectrum. We find that consumer surplus, carrier surplus, and smartphone firms' total variable profit all increase. The change in total welfare is the sum of these increases minus the fixed cost of the added product. We find that the former is about 2.3 times the lower bound of the latter. Therefore, as long as the fixed cost is not more than 2.3 times its lower bound, total surplus increases. Overall, these counterfactual simulation results suggest that there are too few products under oligopolistic competition.

Turning to the second research question of how a change in competition affects product offerings, we simulate the effect of a hypothetical merger between Samsung and LG in March 2013. We also repeat the simulation for a Samsung-Motorola merger and an LG-Motorola merger. Different from addressing the first research question, for which we only need to compute the new pricing equilibrium given certain product offerings in the market, we now need to compute the post-merger equilibrium in both product choice and pricing. Computing the product-choice equilibrium is challenging because, in theory, a firm can drop any subset of its current products or add any number of new products after a merger, leading to a large action space. To keep the problem tractable, we restrict the set of potential products for each firm to those offered by this firm in either February or March 2013, plus two additional products that vary in quality. Even with this restriction, a firm's action space can still be prohibitively large. For example, the merged Samsung-LG entity has 36 potential products, implying a choice set of 2^{36} ($\approx 6.9 \times 10^{10}$) product portfolios. Therefore, to further deal with this computational challenge, we use a heuristic algorithm to find a firm's best-response product portfolio given the portfolios of its competitors, and embed this optimization algorithm in a best-response iteration to solve for the post-merger product-choice equilibrium. Results from Monte Carlo simulations show that our algorithm performs well at least for optimal product portfolio problems with a small number of potential products.[2]

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

In summary, we find that there are too few products in the market. We also find that a reduction in competition as a result of a merger further decreases product variety. These findings are robust to an extensive list of variations to the demand side of the model, to the supply side and to the merger simulation specifications.

By studying the welfare implications of product proliferation and how competition affects them, this paper contributes to the literature of endogenous product choice. Examples in this literature include Draganska, Mazzeo and Seim (2009), Fan (2013), Sweeting (2013), Eizenberg (2014), Nosko (2014), Berry, Eizenberg and Waldfogel (2016) and Wollmann (2018).[3] In terms of methodology, the paper is closely related to Eizenberg (2014), which also studies multi-product firms' discrete product choice for a different research question. Thus, both papers face the challenge of computing

[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 1.06% even as we increase the number of potential products to 10.

[3] Other examples include Seim (2006), Watson (2009), Chu (2010), Crawford and Yurukoglu (2012), Crawford, Shcherbakov and Shum (2018), Orhun, Venkataraman and Chintagunta (2015) and Hristakeva (2018). See Crawford (2012) for a survey of this literature. Examples in the theoretical literature on this topic include Johnson and Myatt (2003) and Shen, Yang and Ye (2016).

an equilibrium where firms have a large discrete choice set in the counterfactual simulations. We tackle the problem using different approaches though. Eizenberg (2014) directly restricts the firms' choice set to the extent that there are only 512 possible equilibrium configurations. This approach is reasonable in his setting because Eizenberg (2014) studies the effect of removing a product. It is therefore plausible to assume that products that are not close substitutes do not adjust. Our paper focuses on mergers. It is unclear, ex ante, which products are unlikely to be adjusted. We thus take a different approach as explained before. In terms of topics, this paper is closely related to Fan (2013), which also studies the effect of a merger considering firms' endogenous product choices. However, whereas Fan (2013) keeps the number of products fixed, our model allows firms to adjust both the number and composition of products after a merger. Interestingly, despite the differences in focus and industries, the two papers make similar policy recommendations: merger policies may need to be tougher when we take into account firms' post-merger adjustments in their product portfolios, whether such adjustments only concern the characteristics of a fixed set of products or also involve changes in the number of products. By contrast, Wollmann (2018) finds that product adjustments mitigate the negative merger effect in the commercial truck industry, while we find that they exacerbate it in the smartphone industry. Note that both papers find product exits by the merging parties and product entries by non-merging firms. The difference is about the net change in product offerings. One potential explanation for the difference is that the commercial truck industry is segmented by gross vehicle weight rating.[4] In such a market, the merged firm would hold near monopoly power in some segments and earn high markups if there were no product adjustments. Other firms thus have strong incentives to enter these segments, which alleviates the harm of the merger. The smartphone market, on the other hand, is much less segmented. Though the overall market is quite concentrated with the top four smartphone firms accounting for about 80% of the total sales, a merger does not dramatically increase concentration (and thus does not generate strong entry incentives) in any well-defined "segment". As a result, the incentive to avoid cannibalization dominates, and the merged firm drops more products than what other firms add. Therefore, due to these differences in market structure, Wollmann (2018) is more about the potential entry defense used in antitrust and this paper is more about an antitrust authority's concern regarding the (potentially negative) merger effect on product variety.

This paper is also related to the stream of research that studies the smartphone industry. For example, Sinkinson (2014) studies the motivations behind the exclusive contract between Apple and AT&T for the early iPhones. In another study, Zhu, Liu and Chintagunta (2015) quantify the welfare effects of this exclusive contract. Luo (2018) examines the operation system network effect. Yang (2018) studies the effect of vertical integration on innovation in the smartphone industry and its upstream chipset industry. Finally, Wang (2018) studies how a Chinese policy that induced

[4]According to Wollmann (2018), "GWR [gross vehicle weight rating] determines the possible uses of a vehicle. Since carrying loads in excess of it is illegal and unsafe, and since it increases price, buyers purchase vehicles with the minimum GWR that safely covers their needs."

fringe entry affects incumbent firms' product portfolio choices in the Chinese smartphone market. We complement these papers by studying the welfare implications of product choices and the effects of competition with endogenous product choice.

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

2 Data

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

The price information provided by the ITG for the four major national carriers (AT&T, Verizon, Sprint, and T-Mobile) is the so-called subsidized price or the average price for a smartphone device that a carrier charges a consumer who uses this carrier's network service.[5] Note that the subsidized price for a smartphone is not the true cost of buying the smartphone because the consumer also needs to pay for the service plan. As will be explained later, we include carrier/year-specific fixed effects in the model to capture the average service cost for a consumer.

Furthermore, since non-major or fringe carriers serve only one regional market and often provide only prepaid service plans, we drop these observations from our analyses.[6] In the end, our sample consists of 3256 observations, each of which is a smartphone/carrier/month combination. The left panel of Table 1 presents the summary statistics on the quantity, price and product characteristics. The average monthly sales of a product are around 77,000 while the standard deviation of the monthly sales is about twice the mean. There is also a sizable variation in price across observations: the price is 122 dollars on average, with a standard deviation of 85. For each product, we observe product characteristics such as battery talk time, camera resolution, screen size measured by the diagonal length of the screen, and weight. We also observe the generation of the chipset used by each product. For example, there are five Apple smartphones in our data (i.e., iPhone 3G, iPhone 3Gs, iPhone 4, iPhone 4s and iPhone 5), each of which uses a chipset of a different generation. The standard deviations of these product characteristics are about 17% to 47% of their corresponding means, indicating a wide variety of products across our sample.

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

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

Table 1: Summary Statistics

Variable	Overall				Choice-set Variation Across Time		
	Mean	S.D.	Min	Max	SD in Mean[c]	S.D. in Min[d]	S.D. in Max
Quantity (1000)	77.54	146.04	0.04	1419	6.49	0.13	63.40
Price ($)	122.16	85.24	0[a]	406.9	22.07	3.23	44.30
Battery talk time (hour)	7.08	2.93	3	22	0.45	0.31	0.91
Camera resolution (megapixel)	4.65	2.18	0[b]	13	0.17	0.14	0.45
Chipset generation 2 dummy	0.23	0.42	0	1	0.03	0	0.09
Chipset generation 3 dummy	0.25	0.43	0	1	0.03	0	0.09
Chipset generation 4 dummy	0.14	0.34	0	1	0.02	0	0.09
Chipset generation 5 dummy	0.09	0.29	0	1	0.02	0	0.07
Screen size (inch)	3.44	0.73	2.20	5.54	0.24	0.22	0.33
Weight (gram)	135.31	22.72	89.5	193	12.70	9.23	17.03
# of smartphone/carrier/months		3256					
# of months						51	

[a]Four observations in our sample have a 0 price.
[b]One product in our sample (BlackBerry 8830) does not have a camera.
[c]Standard deviation of $X_t = \frac{1}{\#\mathcal{J}_t} \sum_{j \in \mathcal{J}_t} x_{jt}$, where j is a smartphone/carrier, t is a month and $\mathcal{J}_t$ is set of observations in month t.
[d]Standard deviation of $X_t = \min\{x_{jt}, j \in \#\mathcal{J}_t\}$.

As will be explained later in Section 4, our identification relies on variations in consumers' choice set. In the right panel of Table 1, we show such variations. Specifically, for each product characteristic and each month, we compute the mean, the minimum and the maximum across all products in this month. We then compute and report the standard deviations of these three statistics across months. These standard deviations in product characteristics in the right panel of Table 1 indicate that the set of products that consumers face change over time. In addition, the number of products changes over time with a mean of 54.55 and a standard deviation of 16.09.

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

To see the variation of the multiple products offered by a smartphone firm in quality and price, in Table 3, we report two within-(firm/month) dispersion measures for price and product characteristics. Take price as an example. First, we compute the difference between the highest and the lowest price among all observations of a given firm/month combination. We then take the average of these differences across all 557 firm/months in the sample to obtain the average range within a firm/month, and report it in Column 1 of Table 3. In Column 2, we report a different measure for the within-(firm/month) dispersion. Specifically, we first compute the standard deviation of price across all observations in the same firm/month. We set the standard deviation to 0

Table 2: List of Top Six Smartphone Firms

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

[a]Averaged across months.

for firm/months with a single observation. We then take the average of these standard deviations across firm/months in the sample, and report the average in Column 2.

We find that the average within-(firm/month) standard deviation in price is 42.42 dollars, which is about 1/2 of the overall standard deviation of price across all observations (see Table 1), implying that within-(firm/month) variation is an important component of total price variation. The within-(firm/month) variation of product characteristics is also significant. For example, Column 1 for chipset generation shows that smartphone firms on average simultaneously offer products whose chipsets are one generation apart.

The first two columns of Table 3 show the within-firm/month variation. In Column 3, we decompose it into that within a carrier and that across a carrier, and show the latter. Specifically, we follow the idea of variance decomposition by first computing the average within a firm/carrier/month and then taking the standard deviation of this average across carriers within a firm/month. For each firm/month, we obtain such a standard deviation of the mean. We report the average of this standard deviation across all firm/months in Column 3. This column indicates that there is significant variation across carriers within the same firm/month.

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

	Average Range[a]	Average S.D.[b]	Average Cross-Carrier S.D.[c]
Price ($)	122.5	42.42	30.93
Battery talk time (hour)	3.10	1.04	0.74
Camera resolution (megapixel)	2.16	0.81	0.45
Chipset generation	0.93	0.36	0.18
Screen size (inch)	0.61	0.21	0.13
Weight (gram)	32.23	11.12	6.67

[a]Average of X_{mt} where $X_{mt} = \max_{j\in\mathcal{J}_{mt}} x_{jt} - \min_{j\in\mathcal{J}_{mt}} x_{jt}$, where j is a smartphone/carrier, t is a month and $\mathcal{J}_{mt}$ is the set of observations of smartphone firm m in month t.

[b]Average of X_{mt} where X_{mt} = (standard deviation of x_{jt} across $j \in \mathcal{J}_{mt}$).

[c]Average of X_{mt} where X_{mt} = (standard deviation of $\frac{1}{\#\mathcal{J}_{mct}} \sum_{j\in\mathcal{J}_{mct}} x_{jt}$ across carriers indexed by c), where $\mathcal{J}_{mct}$ is the set of products of smartphone firm m and carrier c in month t.

3 Model

3.1 Demand

We use a random-coefficient discrete choice model to describe smartphone demand. Since our data are aggregated to the smartphone/carrier/month level, we assume that a consumer's choice is a smartphone/carrier combination, indexed by j. Furthermore, we assume that the utility that consumer i gets from purchasing j in period t is:

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

where q_j is a quality index which depends on the observable product characteristics $\boldsymbol{x}_j$ as $q_j = \boldsymbol{x}_j \boldsymbol{\theta}$, where $\boldsymbol{\theta}$ are parameters to be estimated. In other words, we assume that the consumer utility depends on the product characteristics only through the quality index. This parsimonious functional form allows us to estimate the heterogeneous preferences for all important phone characteristics even if some of the characteristics' own random coefficient variances cannot be estimated precisely, due to lack of variation, if we allow each characteristic to have an independent random coefficient.[7] In Appendix B, we conduct a robustness analysis where we use the baseline estimates but assume that the coefficients are independent across characteristics. We find our results are robust.

In the utility function (1), the random coefficient β_i captures consumers' heterogeneous tastes for quality and is assumed to follow a normal distribution with mean β and variance σ^2. Since we cannot separately identify β, σ and $\boldsymbol{\theta}$ as they enter the utility function as $\beta\boldsymbol{\theta}$ and $\sigma\boldsymbol{\theta}$, we normalize the first element of $\boldsymbol{\theta}$ to be 1. Finally, we denote the price of j in period t by p_{jt}.

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

[7]Note that while there is variation in product characteristics across observations, the variation is correlated among the characteristics. For example, the correlation between camera resolution and screen size is 0.8, and the correlation of both camera resolution and screen size with chipset generation is also around 0.8. Such correlations make identifying a different random coefficient for each product characteristic in the quality index difficult. On the supply side, while this assumption allows us to describe a product by its quality index (and the brand and carrier), it means the model cannot be used to discuss firms' specialization strategy such as whether to increase the battery life time or camera resolution.

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

the mean utility of the outside option to be 0. Thus, the utility of the outside option is $u_{i0t} = \varepsilon_{i0t}$.

Under the type-I extreme value distributional assumption of ε_{ijt}, we can express the market share of choice j in period t as:

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

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

We define the mean utility of j in period t as

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

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

3.2 Supply

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

3.2.1 Decision on Prices

In the final stage of our model, carriers choose retail prices after observing the set of products available on each carrier (denoted by $\mathcal{J}_{ct}$), wholesale prices (w_{jt}) and demand shocks (ξ_{jt}). Suppose that the profit that carrier c obtains through its service is b_{ct} per consumer.[9] Thus, carrier c's profit for each unit of a product sold is $p_{jt} + b_{ct} - w_{jt}$. We do not observe b_{ct} or w_{jt}. However, we can invert out $\tilde{w}_{jt} = w_{jt} - b_{c(j)t}$ from the first-order condition on p_{jt}. Specifically, carrier c's profit-maximizing problem is

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

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 $(\boldsymbol{q}_t, \boldsymbol{\xi}_t)$ are analogously defined in Section 3.1.

[9] We do not allow this service profit to vary across products because we cannot separately identify it from the cost shock as both would vary at the jct level. This is clear from equation (6) later in this section. Therefore, our estimated b_{ct} is the average per-consumer service profit.

In the second stage, smartphone firms choose wholesale prices that they charge carriers after observing demand and marginal cost shocks. We assume that marginal cost depends on product quality (q_j), carrier/year fixed effects (γ_{ct}), and a jt-specific shock (η_{jt}).[10] Specifically, we assume that the marginal cost is $mc_{jt} = \gamma_{c(j)t} + \gamma_1 exp\left(q_j\right) + \eta_{jt}$.[11] If we let $\tilde{mc}_{jt} = mc_{jt} - b_{c(j)t}$ and $\tilde{\gamma}_{c(j)t} = \gamma_{c(j)t} - b_{c(j)t}$, we have:

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

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

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

where $\mathcal{J}_{mt}$ represents the choices offered by firm m in period t. 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,

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

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

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

which we bring to data for estimation.

As can be seen from equation (10), this pricing model is a simple linear pricing model, which implies double marginalization and rules out quantity discounts. In Supplemental Appendix SA, we consider four alternative pricing models such as non-linear pricing models or a joint price setting model for robustness analyses.

3.2.2 Decision on Products

In the first-stage of the model, smartphone firms choose products. In other words, we assume that the upstream firm makes the product decision, in contrast to Eizenberg (2014). Note that in the PC market studied in Eizenberg (2014), the upstream firms (i.e., the CPU manufacturers)

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

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

produce only a component of the final product. Therefore, it seems natural to assume that the downstream firms make a product decision in the PC market. In our setting, however, the upstream firms make the final products directly, and it seems more natural to assume that they make the product decisions.[12] Nash equilibrium implies that given competitors' product portfolios at the equilibrium, any deviation from a smartphone firm's equilibrium product portfolio should not lead to a higher expected profit for this firm, where the expectation is taken over demand and marginal cost shocks. Specifically, we consider two types of deviations: removing a product in the data or adding a product not in the data. Note that while the majority of the products in our study are sold through only one carrier, 12% are sold through multiple carriers. Therefore, to distinguish a smartphone/carrier combination (indexed by j) from a smartphone product, we index the latter by $\tilde{j}$. Similarly, $\tilde{\mathcal{J}}_{mt}$ represents all smartphones of m, i.e., m's product portfolio; and $\tilde{\mathcal{J}}_t$ represents all smartphones in the market in period t.

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

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

where $\pi_{mt}\left(\boldsymbol{q}_t,\boldsymbol{\xi}_t,\boldsymbol{\eta}_t\right)$ is the equilibrium variable profit for firm m (at the stage-2 and stage-3 pricing equilibrium), $F_{\tilde{j}t}$ is the fixed cost, $\pi_{mt}\left(\boldsymbol{q}_t\backslash q_{\tilde{j}},\boldsymbol{\xi}_t\backslash\xi_{\tilde{j}t},\boldsymbol{\eta}_t\backslash\eta_{\tilde{j}t}\right)$ is firm m's variable profit if product $\tilde{j}$ is removed from its product portfolio, and $F_{\tilde{j}t}$ is the fixed cost.[13] Inequality (11) gives an upper bound of $F_{\tilde{j}t}$ for $\tilde{j}t$ in the data. Intuitively, for products in the market, their fixed costs should be bounded from above.

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

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

This inequality yields a lower bound of $F_{\tilde{j}t}$ for any $\tilde{j}t$ such that $\tilde{j}\notin\tilde{\mathcal{J}}_t$. This is again intuitive because the fixed cost of a not-offered product should be bounded from below. Note that such

[12] In reality, downstream carriers may be able to influence upstream smartphone firms' product choice directly. We believe our model is nonetheless a parsimonious way to capture the product decision in this industry. For example, if a carrier does not want to sell a specific product from a smartphone firm, in our model, the carrier can set the retail price to infinity to achieve that. On the other hand, if a carrier wants to sell a product from a smartphone firm, this carrier and the smartphone firm should be able to reach an agreement to make it profitable for the smartphone firm to produce this product. Such an agreement may involve non-linear pricing, which we study in our robustness analyses in Supplemental Appendix SA.2.

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

a potential product $\tilde{j}$ can be any product not in the data. In Sections 4 and 5, we explain the potential products we consider in the estimation and the counterfactual simulations.

4 Estimation

4.1 Estimation Procedure

The estimation of demand and marginal costs is similar to that in Berry, Levinsohn and Pakes (1995). We construct moments using equations (3) and (10), and estimate the parameters using the Generalized Method of Moments. Following the literature, our instrumental variables are based on the characteristics of other products of the same firm or the products of the competing firms. This estimation strategy relies on the timing assumption that the demand and marginal cost shocks are realized after the product choice.[14] Note that we control for systematic brand effects, carrier effects, and time effects using various fixed effects. Therefore, it seems reasonable (though imperfect) to assume that any product/month-specific shocks are uncorrelated with product characteristics.[15] In addition to the above instruments, we include the four-month lagged exchange rates of the Chinese, Japanese and Korean currencies to U.S. dollars as a cost shifter in the instruments. The market size used in the estimation is 30 million, about 10% of the U.S. population during the sample period. Our results are robust to other market size measures.

As for the fixed cost, we use inequalities (11) and (12) to obtain the bounds. Using inequality (11), we calculate the upper bound of $F_{\tilde{j}t}$ as (the opposite of) the change in the expected variable profit when product $\tilde{j}$ is removed, i.e., $E_{(\boldsymbol{\xi}_t,\boldsymbol{\eta}_t)}\pi_{mt}\left(\boldsymbol{q}_t,\boldsymbol{\xi}_t,\boldsymbol{\eta}_t\right)-E_{(\boldsymbol{\xi}_t\backslash\xi_{\tilde{j}t},\boldsymbol{\eta}_t\backslash\eta_{\tilde{j}t})}\pi_{mt}\left(\boldsymbol{q}_t\backslash q_{\tilde{j}},\boldsymbol{\xi}_t\backslash\xi_{\tilde{j}t},\boldsymbol{\eta}_t\backslash\eta_{\tilde{j}t}\right)$. The expectation is taken over the demand and marginal cost shocks $(\boldsymbol{\xi}_t,\boldsymbol{\eta}_t)$. To compute the expected variable profit, we draw these shocks from their empirical distributions. We first compute the pricing equilibrium and calculate the resulting variable profit for each draw, and then take the average of these variable profits across all draws. Using inequality (12), we calculate the lower bound similarly for any $\tilde{j}t$ such that $\tilde{j}\notin\tilde{\mathcal{J}}_t$.

4.2 Estimation Results

Table 4 reports the estimation results on demand and marginal cost. Our demand estimation results indicate that consumers on average favor products with longer battery talk time, higher camera resolution, a more advanced chipset, a larger screen and a lighter weight. For example, we find that a one-hour increase in battery talk time is equivalent to a price decrease of 8.4 dollars for an average consumer. Similarly, a one-megapixel increase in camera resolution is equivalent to a

[14] Similar timing assumption is made in, for example, Eizenberg (2014) and Wollmann (2018).

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

Table 4: Estimation Results

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

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

price decrease of 13.9 dollars, while an increase in the screen size by 0.1 inches is equivalent to a price decrease of 15 dollars. Finally, we find that each generation upgrade is equivalent to a price drop between 35 to 93 dollars. The estimated standard deviation of consumers' taste for quality is about 40% of the average taste, suggesting that consumers are heterogenous in their willingness-to-pay for quality. In our estimation, we include Apple, BlackBerry and Samsung dummies and group all other brands as a baseline brand in the utility function. Our estimates show that there is a large premium for Apple (417 dollars), followed by BlackBerry, and then Samsung.[16] 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.[17]

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

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

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

table shows that a $10 increase in the price of a product leads to about 6% decrease in its demand.[18] Unsurprisingly, the own price semi-elasticities are larger than the cross semi-elasticities.

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

Table 5: Demand Semi-Elasticities with Respect to Price

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

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

Table 6: Demand Elasticities with Respect to Quality

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

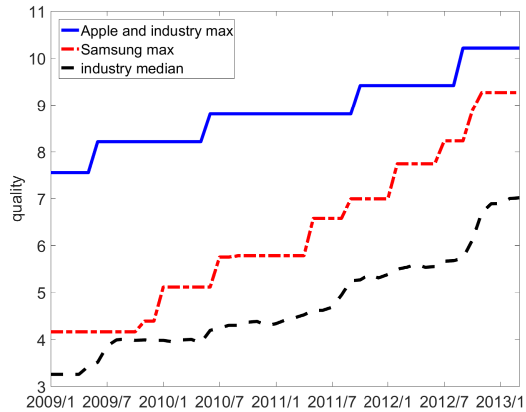
Note: Top-five products on AT&T in March 2013. (Row i, Column j): percentage change in market share of product j with a 1 percent change in product i's quality.

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

The number of smartphones also increases over time. However, such an increase does not necessarily lead to an increase in product variety. For example, if firms use a strategy of obfuscation,

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

Figure 1: Smartphone Quality over Time



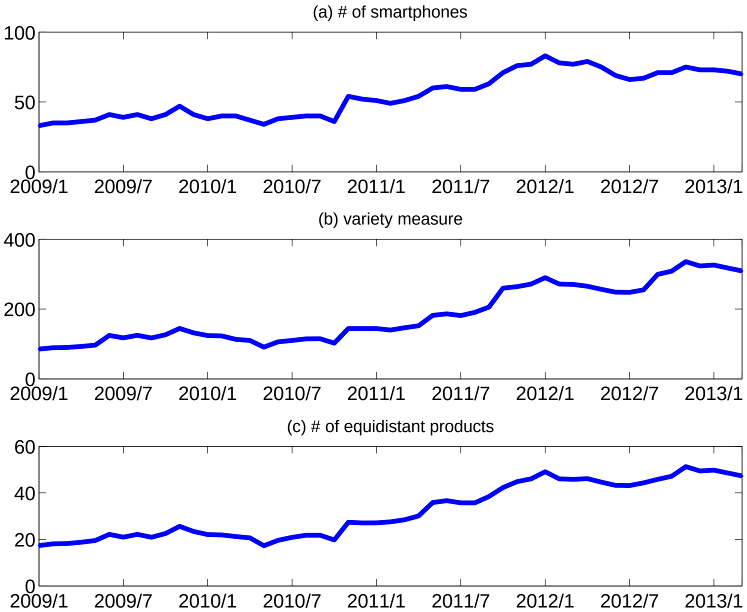
Note: This figure plots the quality frontier of Apple and Samsung over time. It also plots the highest and the median quality across all products in each month. The former coincides with the quality frontier of Apple.

i.e., they add products that differ from existing products only in trivial features such as names or colors, this does not really contribute to product variety. To show the evolution of product variety over time, we use the same quality index used in Figure 1 to construct a measure of product variety. Specifically, we measure product variety in a market with n products as $\left[\sum_{k=2}^{n}\left(q^{(k)}-q^{(k-1)}\right)^{1/2}\right]^{2}$, where $q^{(1)}<\cdots<q^{(n)}$ are the qualities of the n products sorted in an ascending order. Note that this measure resembles the CES utility function, and has three desirable properties. First, given the quality range (i.e., $q^{(n)}-q^{(1)}$) and the number of products n, this measure is maximized when products are equidistant. The maximum is $(n-1)\left(q^{(n)}-q^{(1)}\right)$. Second, this maximum is increasing in the number of products n and the quality range $\left(q^{(n)}-q^{(1)}\right)$. Third, adding a product identical to one of the existing products in terms of the key observable characteristics (and hence also in terms of the quality index) has no impact on the product variety measure.

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

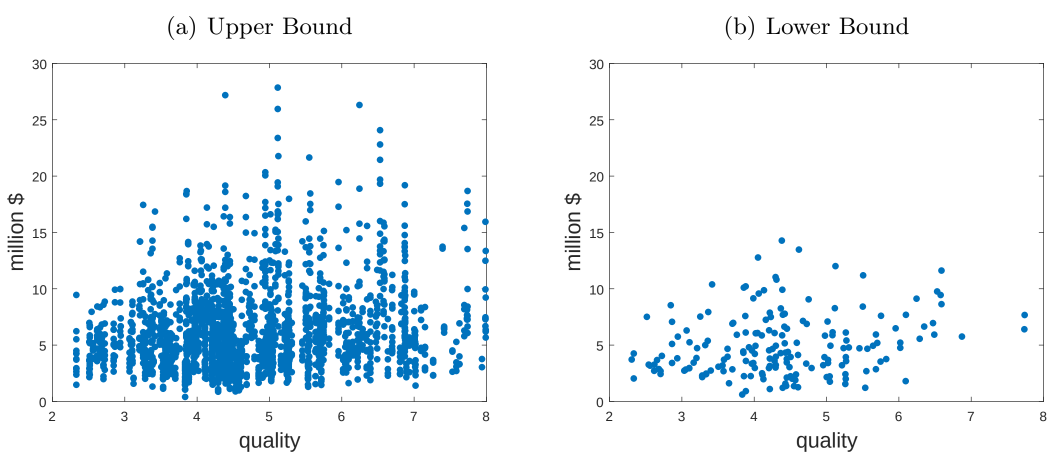
Note that while our product variety measure is a simple way to capture product variety and distinguish meaningful product variety from obfuscation, it is not necessarily a good measure for welfare. In other words, consumer surplus is not necessarily monotonic in it. That is why in all counterfactual simulations in Section 5, we report welfare measures in addition to the variety measure.

Figure 2: Product Variety over Time



On the supply side, we find that marginal cost increases in product quality. Based on the estimates of the demand and marginal cost functions, we obtain the fixed cost bounds. As mentioned, we can obtain an upper bound for each product in the data and a lower bound for any product not in the data. Figure 3 plots the upper bound of the fixed cost for non-flagship smartphone/month combinations in the data (in Figure 3(a)) and the lower bound for discontinued non-flagship products (in Figure 3(b)). The horizontal axis represents the quality of a product, the same quality index in Figure 1. The vertical axis represents the bound of the fixed cost. Figure 3 suggests that the bound of the fixed cost is positively correlated with product quality. The average upper bound in Figure 3(a) is 6.19 million dollars; and the average lower bound in Figure 3(b) is 5.00 million dollars.

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



5 Counterfactual Simulations

In this section, we conduct counterfactual simulations to address the two research questions of interest. As mentioned, there are 39 flagship smartphones in our data. Flagship products are usually equipped with cutting-edge technologies and thus require a sizable sunk innovation cost. Our static model of product choice, which focuses on product variety instead of product innovation, thus is most suitable to describe firms' decision on non-flagship products given the quality frontier. Therefore, in this section, we focus on non-flagship products in our baseline and show the robustness of our results as we add flagship products into consideration.

5.1 Are there too few or too many products?

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

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

Removed product	Lowest-quality	Median	Highest
Δ(consumer surplus)	-1.10	-3.29	-13.08
Δ(carrier surplus)	-1.01	-1.48	-11.18
Δ(sum of smartphone firms' variable profits)[a]	-0.56	-1.14	-4.41
Upper bound of savings in fixed costs[b]	1.11	2.65	14.20

[a] $\sum_m \left[E_{\left(\boldsymbol{\xi}_t \backslash \xi_{\tilde{j}t}, \boldsymbol{\eta}_t \backslash \eta_{\tilde{j}t}\right)} \pi_{mt}\left(\boldsymbol{q}_t \backslash q_{\tilde{j}}, \boldsymbol{\xi}_t \backslash \xi_{\tilde{j}t}, \boldsymbol{\eta}_t \backslash \eta_{\tilde{j}t}\right) - E_{(\boldsymbol{\xi}_t, \boldsymbol{\eta}_t)} \pi_{mt}\left(\boldsymbol{q}_t, \boldsymbol{\xi}_t, \boldsymbol{\eta}_t\right) \right]$, where $\tilde{j}$ is the dropped product.

[b] $E_{(\boldsymbol{\xi}_t, \boldsymbol{\eta}_t)} \pi_{mt}\left(\boldsymbol{q}_t, \boldsymbol{\xi}_t, \boldsymbol{\eta}_t\right) - E_{\left(\boldsymbol{\xi}_t \backslash \xi_{\tilde{j}t}, \boldsymbol{\eta}_t \backslash \eta_{\tilde{j}t}\right)} \pi_{mt}\left(\boldsymbol{q}_t \backslash q_{\tilde{j}}, \boldsymbol{\xi}_t \backslash \xi_{\tilde{j}t}, \boldsymbol{\eta}_t \backslash \eta_{\tilde{j}t}\right)$, where m is the firm of the dropped product.

The results across all three columns of Table 7 show that consumers are worse off when a product is removed: consumer surplus decreases by 1.10, 3.29 and 13.08 million dollars in the lowest-, median- and highest-quality scenarios, respectively. Note that the revenues generated by these products in March 2013 are, respectively, 8.19, 32.26 and 66.39 million dollars, about 5 to 10

[19] As mentioned in Footnote 13, for any product removed, we remove it from all carriers. Our finding is robust to removing a smartphone/carrier combination instead.

times the consumer surplus changes from removing the corresponding product.[20] Such decreases in consumer welfare are partially due to changes in prices after a product is a removed, but mainly because of the direct effect of removing the product. Specifically, when we hold the prices of the remaining products fixed, we find that changes in consumer surplus are (-1.12, -2.65, -12.49) million dollars across the three columns, which accounts for most of the total change in consumer surplus.

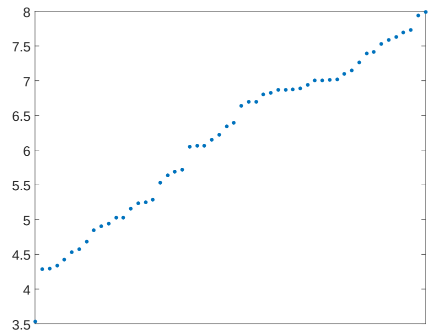
Carriers' profits also drop. As for smartphone firms, the comparison of the third row and the last row shows that if the fixed cost is at its upper bound, the total smartphone producer surplus increases after a product is removed. This result confirms the intuition that because firms do not internalize the business stealing effect, there may be excessive product proliferation, especially if the fixed cost is high. However, this effect is dominated by the effect of product offerings on consumer surplus: summing over the four rows of Table 7, we see that removing a product leads to a decrease in total welfare, even considering the maximum possible saving in the fixed cost. One concern with this finding is that the decrease in consumer surplus may be overestimated because when we remove a product, we also remove the Logit error term corresponding to this product, which is independent of other Logit error terms. To address this concern, we recalculate Δ(consumer surplus) without accounting for changes in the set of Logit error terms (see Supplemental Appendix SC for details). The changes in consumer surplus without changes in Logit error terms are indeed smaller: they become -0.45, -2.33, and -10.25 million dollars. However, the sum of the four rows is still negative.

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

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

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

Figure 4: Quality of Products in March 2013



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

Table 8: Welfare Changes When a Product Is Added, March 2013 (million $)

	HTC	LG	Motorola	Samsung
Δ(consumer surplus)	2.26	2.28	2.37	2.69
Δ(carrier surplus)	1.20	1.21	1.26	1.52
Δ(sum of smartphone firms' variable profits)[a]	0.92	0.91	0.86	1.44
Lower bound of added fixed costs[b]	1.92	1.93	1.97	2.45

[a] $\sum_m \left[E_{\left(\boldsymbol{\xi}_t\cup\xi_{\tilde{j}t},\boldsymbol{\eta}_t\cup\eta_{\tilde{j}t}\right)}\pi_{mt}\left(\boldsymbol{q}_t\cup q_{\tilde{j}},\boldsymbol{\xi}\cup\xi_{\tilde{j}t},\boldsymbol{\eta}_t\cup\eta_{\tilde{j}t}\right) - E_{(\boldsymbol{\xi}_t,\boldsymbol{\eta}_t)}\pi_{mt}\left(\boldsymbol{q}_t,\boldsymbol{\xi}_t,\boldsymbol{\eta}_t\right)\right]$, where $\tilde{j}$ is the added product.

[b] $E_{\left(\boldsymbol{\xi}_t\cup\xi_{\tilde{j}t},\boldsymbol{\eta}_t\cup\eta_{\tilde{j}t}\right)}\pi_{mt}\left(\boldsymbol{q}_t\cup q_{\tilde{j}},\boldsymbol{\xi}\cup\xi_{\tilde{j}t},\boldsymbol{\eta}_t\cup\eta_{\tilde{j}t}\right) - E_{(\boldsymbol{\xi}_t,\boldsymbol{\eta}_t)}\pi_{mt}\left(\boldsymbol{q}_t,\boldsymbol{\xi}_t,\boldsymbol{\eta}_t\right)$, where m is the firm of the added product.

Not surprisingly, consumers are better-off with the additional product in the market (Row 1). Carriers also earn more profits (Row 2). Smartphone firms' total variable profit increases (Row 3). For the added product, we obtain a lower bound on its fixed cost, which is reported in Row 4 of Table 8. According to inequality (12), Row 4 is the increase in the variable profit of the firm who is adding the product. It is reassuring that it is always larger than the change in the sum of all firms' variable profits (Row 3), as expected when there is business stealing. In other words, while Row 3 indicates an increase in the sum of smarpthone firms' variable profits, the difference between Rows 3 and 4 indicates a decrease in the sum of their total profits even considering the lower bound of fixed cost of the added product.

In sum, consumers and carriers are better off while the sum of smartphone firms' profits decreases. The change in total welfare is the sum of the first three rows minus the fixed cost of the added product. We find that the former is about 2.3 times the lower bound of the latter for all four simulations. This implies that as long as the fixed cost is not more than 2.3 times of its estimated lower bound, the change in total welfare is positive. Table 8 suggests that this is mainly because a firm does not take into account the increase in consumer surplus when making a decision. To put the number 2.3 in perspective, note that the average upper bound and the average lower bound we report in Section 4 are, respectively, 6.19 and 5.00, with a ratio of 1.2. When we replace Δ(consumer surplus) in Row 1 by that without accounting for changes in Logit error terms, the ratio of the sum of the first three rows to the lower bound of the fixed cost varies 1.9 and 2 (across all four columns), which is still above 1.2. Note that as mentioned in Section 4, the average upper bound is averaged over the existing products and the average lower bound is averaged over the discontinued products. Therefore, they are not directly comparable. That said, we think it is still informative to report the ratio of them. For example, if the ratio were larger than 2.3, we might conclude that adding the product is unlikely to increase the total surplus.

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

As mentioned, the literature (e.g. Spence (1976) and Mankiw and Whinston (1986)) has identified two countervailing forces determining the efficiency of the equilibrium product offerings in an oligopolistic competition: firms do not consider the business-stealing externality, which may lead to excessive product offerings; firms do not consider consumer surplus, which may lead to insufficient product proliferation. Compared to single-product firms studied in these papers, the multi-product firms in our paper have an additional reason to restrict product offerings: to avoid cannibalization. In fact, we find that all smartphone firms in March 2013 are likely to offer more products if they ignore cannibalization. Specifically, we repeat the counterfactual simulation in Table 8 for all smartphone firms in March 2013. To study firm behavior without the cannibalization consideration, we now focus on "product variable profit" (π_{jt}) instead of "firm variable profit" ($\pi_{mt} = \sum_{j \in \mathcal{J}_{mt}} \pi_{jt}$). If a firm ignores cannibalization, it would want to add the product if $\pi_{jt} > F_{jt}$. We find that, across all smartphone firms, the ratio of the added product's variable profit to the lower bound of its fixed cost varies from 2.28 to 2.31, implying that as long as the fixed cost is not more than 2.28 times of its lower bound, all smartphone firms in March 2013 would want to deviate from their current product portfolios by adding the product studied in Table 8. This result suggests that firms' cannibalization concerns indeed motivate firms to restrict product offerings, which partially contributes to our finding that there are too few products in the market.[21]

5.2 How does competition affect product offerings?

To study how competition affects product offerings, we simulate the effect of a hypothetical merger between Samsung and LG in March 2013,[22] the second and the third largest smartphone firms in terms of sales in that month, following Apple. In Appendix B, we show the effects of a Samsung-Motorola merger and an LG-Motorola merger, where Motorola is the fourth largest smartphone firm in March 2013. In these merger simulations, we compute the post-merger equilibrium in both product offerings and pricing. In contrast, in Section 5.1, we only need to compute the new pricing equilibrium for given product offerings in the market.

Computing the post-merger product-choice equilibrium can be challenging because a firm can choose to drop any set of products or add any number of products after a merger, leading to a potentially very large action space for product choice. To keep the problem tractable, we restrict the set of potential products for each firm in the merger simulations to be the firm's products in the data in either March or February 2013, plus two additional potential products that fill gaps in the quality spectrum.[23] As shown in the plot of the qualities of products in March 2013 (Figure 4), the quality spectrum exhibits gaps between 5.72 and 6.05 and between 6.40 and 6.64. We find the respective midpoints of these gaps (5.88 and 6.52) and allow each firm to add a product at either or both of these qualities. These two products can be sold through any of the four carriers in the sample. Products in February or March 2013 are sold through their respective carriers observed in the data. In sum, with this set of potential products, our simulation allows a firm to drop any subset of its existing products, add back any subset of its discontinued products, add one or two additional products, or use a combination of the above three types of adjustments.

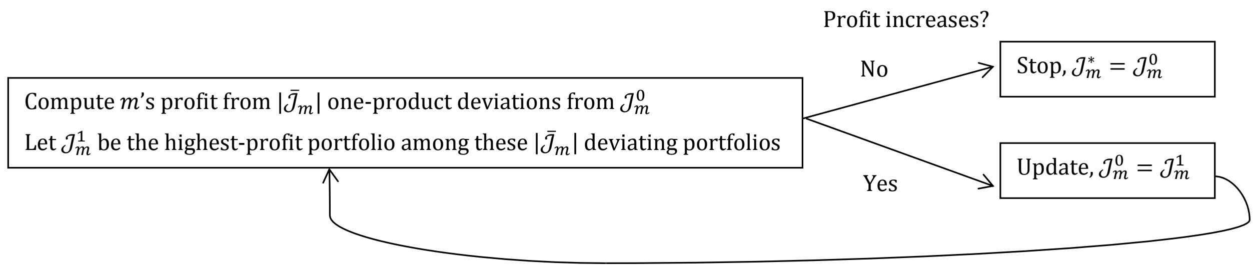
Even with this restricted set of potential products, the action space for a firm can still be too large because a smartphone firm chooses a product portfolio, which is a subset (of any size) of the potential products. In other words, the choice set of a firm is the power set of its potential products. For example, in the baseline when we only consider non-flagship products, the merged Samsung-LG entity has 31 potential products, and thus a choice set of 2^{31} ($\approx 2.4 \times 10^9$) product portfolios. Moreover, to compute the profit of each product portfolio, we need to compute the corresponding

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

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

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

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



pricing equilibrium, making the computational burden prohibitively high. To address this issue, we use a heuristic algorithm to compute a firm's optimal product portfolio given its competitors' product portfolios. This algorithm is then embedded in a best-response iteration to solve for the post-merge product-choice equilibrium.

We use firm m as an example to describe the heuristic algorithm for a firm's optimal product portfolio problem, and depict the algorithm in Figure 5. Let $\bar{\mathcal{J}}_m$ represent firm m's potential products (for example, $\bar{\mathcal{J}}_m = \{j_1, ..., j_n\}$). We start with a portfolio $\mathcal{J}_m^0 \subseteq \bar{\mathcal{J}}_m$ (for example, $\mathcal{J}_m^0 = \{j_1, ..., j_{n_1}\}$ where $n_1 \leq n$). We compute firm m's profit from each of the following deviations from $\mathcal{J}_m^0$: $\mathcal{J}_m^0 \backslash \{j_k\}, k = 1, ..., n_1$ or $\mathcal{J}_m^0 \cup \{j_k\}, k = n_1 + 1, ..., n$. Note that each deviation differs from $\mathcal{J}_m^0$ in only one product: either a product in $\mathcal{J}_m^0$ is removed or a potential product not in $\mathcal{J}_m^0$ is added. Let $\mathcal{J}_m^1$ be the highest-profit deviating product portfolio. If firm m's profit corresponding to $\mathcal{J}_m^1$ is smaller than that corresponding to $\mathcal{J}_m^0$, this procedure stops and returns $\mathcal{J}_m^0$ as the best response. Otherwise, we compute m's profit from any one-product deviation from $\mathcal{J}_m^1$ by either adding a potential product to or dropping a product from $\mathcal{J}_m^1$. We continue this process until firm m's profit no longer increases. This algorithm allows us to translate a problem whose action space grows exponentially in the number of potential products (choosing from $2^{|\bar{\mathcal{J}}_m|}$ product portfolios) into one whose action space grows linearly (in each step, evaluating $|\bar{\mathcal{J}}_m|$ portfolios).[24]

In this algorithm, even though we impose a one-product deviation restriction in each step of the algorithm, the optimal product portfolio found by the algorithm can be very different from the starting portfolio in both product number and composition. This is because each step of the algorithm leads to a one-product deviation and strictly increases profit prior to convergence. Therefore, as long as the algorithm does not converge after only one step, it yields a product portfolio that deviates from the starting product portfolio by more than one product. Note that

[24] Jeziorski (2014) uses a similar idea to avoid an excessive computation burden in studying firm acquisition problems. Specifically, he assumes that when a firm decides on which set of firms to acquire, it makes a sequential decision of whether to acquire each firm according to a pre-specified sequence of potential acquirees. Our algorithm is less restrictive: in each step, a firm evaluates *all* one-product deviations simultaneously rather than being constrained to one such deviation determined by a pre-specified sequence. Jia (2008) also faces a similar large action space problem in studying chain store location choice. She solves the issue by exploiting lattice theory, transforming the profit-maximizing problem into a search for fixed points defined by the necessary optimality conditions. A critical assumption for her approach to work is that the profit of one store increases when the chain opens another store, i.e., stores of the same chain are complementary. Such a complementarity assumption is unlikely to hold in our context of product choice.

product composition can also change if the algorithm drops one product in one step and adds another in a later step.

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

We embed this algorithm in a best-response iteration, where we start with the pre-merger equilibrium and let firms take turns updating to their best-response product portfolio. We repeat this iteration until no firm has an incentive to deviate. Specifically, we loop over firms according to their monthly sales in March 2013, either ascending or descending. These two best-response iterations yield the same equilibrium in our merger simulations. We also use a simultaneous iteration algorithm and again obtain the same equilibrium.

As for fixed costs, we draw the fixed cost for each potential product from a range consistent with the bounds obtained in the estimation and report the average merger effects, averaged over different fixed-cost draws. Specifically, for each product in the data, we have obtained an upper bound of its fixed cost (denoted by $\bar{F}_{\tilde{j}t}$). For such a product, we uniformly draw five fixed-cost values from the range $\left[0.5\bar{F}_{\tilde{j}t}, \bar{F}_{\tilde{j}t}\right]$. Similarly, for each potential product not in the data, we have obtained a lower bound of its fixed cost $\underline{F}_{\tilde{j}t}$. We draw five fixed-cost values from $\left[\underline{F}_{\tilde{j}t}, 5\underline{F}_{\tilde{j}t}\right]$. In Appendix B, we consider two alternative ranges for the fixed costs. In one alternative, we fix the length of the range to be $(\bar{F} - \underline{F})$, where $\bar{F} = 6.19$ and $\underline{F} = 5.00$ are the average upper and lower bounds reported in Section 4. In the other alternative, we define the range according to the quality of a product. Our merger simulation results are robust to these two alternative fixed-cost ranges.

Table 9 presents the baseline merger simulation results. These results show an average decrease of 1.80 products after the merger, mainly driven by the merged firm dropping products: the average change for the merged firm is -2.60 while that for the non-merging firms is 0.80. We also find that the merged firm drops products across the quality spectrum except the very top. Specifically, we find that the average number of products dropped from each quality quartile (below the pre-merger 25% quality quantile, [25%, 50%), [50%, 75%), and above 75%) is 0.2, 0.8, 0.8, and 0, respectively. Overall, the product variety measure decreases by 17.36 (from 360.25). We use the following back-of-the-envelope calculation to understand the magnitude of such a change. Before the merger, the range of the quality spectrum is 6.68. The pre-merger product variety measure (360.25) is "as if" there are 54.93 equidistant products (360.25/6.68 + 1), while the post-merger product variety measure (342.88) is "as if" there are 52.33 equidistant products. Therefore, a change of -17.36 in the product variety measure is equivalent to a decrease of about 2.61 in the number of "as if" equidistant products.

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

	Variable	Pre-merger	Post-merger	Change
(1)	Number of products	70	68.20	-1.80
(2)	merged firm	30	27.40	-2.60
(3)	non-merging firms	40	40.80	0.80
(4)	Variety	360.25	342.88	-17.36
(5)	Sales-weighted avg quality	8.50	8.52	0.02
(6)	merged firm	7.31	7.33	0.02
(7)	non-merging firms	6.229	6.228	-0.001
(8)	Sales-weighted avg price ($)	101.73	103.83	2.10
(9)	merged firm	151.04	163.74	12.70
(10)	non-merging firms	85.24	85.73	0.49
(11)	Total sales	7,205,974	7,116,948	-89,026
(12)	merged firm	1,805,421	1,651,389	-154,032
(13)	non-merging firms	5,400,553	5,465,559	65,005
(14)	Consumer surplus (million $)	1735.41	1706.23	-29.18
(15)	Carrier profit (million $)	1322.66	1305.74	-16.93
(16)	Smartphone firm profit (million $)	1184.26	1198.24	13.98
(17)	merged firm	214.37	215.96	1.59
(18)	non-merging firms	969.89	982.27	12.38

Regarding changes in quality and price, we find little change in the sales-weighted average quality in the market after the merger, but an increase in the sales-weighted average retail price of 2.10 dollars. This is largely due to price increases for the merged firm's products. Specifically, the results in Row (9) of Table 9 show that the sales-weighted average retail price of the merged firm's products increases by about 12.70 dollars. Overall, sales for the merged firm decrease and those for the non-merging firms increase, with a net change of -89,026 units. The decrease in product offerings and the increase in prices eventually lead to a reduction in consumer surplus of around 29.18 million dollars or 1.3%. Carriers are also worse off. The total smartphone profit, however, increases by around 13.98 million dollars, among them, 1.59 million dollars are attributed to the increase in the merged firm's profit and the remaining 12.38 million dollars are due to changes in non-merging firms' profits with an average increase of 1.13 million dollars per non-merging firm. In sum, overall welfare decreases by around 32.13 million dollars or 1%.

Altogether, the results from this counterfactual simulation show that a reduction in competition leads to a decrease in the number of products across the quality spectrum. This decrease is accompanied by an increase in prices, leading to a decline in consumer and carrier surplus and eventually a reduction in overall welfare, despite an increase in smartphone producer surplus. Our simulations of other mergers yield similar results (see Appendix B for the Samsung-Motorola and LG-Motorola merger). The combination of our findings in the previous section (i.e., the market contains too few products) and our findings in this section (i.e., a merger further reduces product offerings) suggests that merger policies in this market may need to be stricter when we take into account the effect of a merger on product offerings.

This conclusion is consistent with a comparison of our merger simulation with one where we keep the set of products fixed and allow firms to adjust only prices after the merger. In the latter merger simulation, we find that the changes in consumer surplus, carrier profit, and smartphone firm profit are all smaller (in absolute value). They are -20.66, -12.24 and 10.31 million dollars, respectively. In contrast, they are -29.18, -16.93 and 13.98 million dollars when post-merger adjustments in both product offerings and prices are allowed. The decrease in total surplus is also smaller (-22.59 vs. -32.13), again suggesting that product adjustments exacerbate the negative merger effect.

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

6 Discussion

Our results are robust to a host of variations in demand and pricing model specifications. In particular, we find that the assumption of independent idiosyncratic taste shocks does not drive our welfare results. We also find that our results are robust to various nonlinear pricing models.[25]

Before concluding, we now provide a discussion on the approach in our welfare analyses. In our first set of welfare analyses where we drop products, we use the upper bounds of these products' fixed costs directly. The key advantage is that we do not make assumptions about the parametric functional form of the fixed cost and about its error terms. In these counterfactual simulations, we obtain an upper bound on the welfare change. We find that even the upper bound is negative, which means we can conclude that dropping a product reduces welfare without imposing much structure on the fixed cost.

However, knowing one bound is not enough for our other counterfactuals. In the second set of counterfactual simulations where we add a product, we find the upper bound of welfare change to be positive, which does not give us a definitive answer on the actual welfare change. This is fundamentally a selection problem: the fixed costs of the products not in the data tend to be high and could, in theory, be infinity, and the resulting welfare change when adding the product would be negative. To deal with this selection problem, Berry, Eizenberg and Waldfogel (2016) obtain two-sided bounds of fixed costs by grouping products into a relatively small number of "categories". Specifically, they assume that the fixed cost is format-quality-market specific and does not vary across firms or products. As a result, the conditions of positive profits for the current entrants and no profitable additional entry give them two-sided bounds. Pakes, Porter, Ho and Ishii (2015) assume the fixed cost is firm specific and deal with the selection issue by either relying on a symmetry assumption or using an instrumental variables approach. Finally, Eizenberg (2014) assumes that the fixed cost of each product is a firm-specific fixed cost plus a product-specific shock,

[25] In the interest of space, we present these robustness analyses in Supplemental Appendix SA.

and leverages assumptions on the support of the fixed cost distribution to obtain an estimated set for each firm's average fixed cost. While allowing the fixed cost to be product specific in estimation, Eizenberg (2014) sets the product-specific shock to be zero, which means that the fixed cost is firm specific, in the counterfactual simulations.

In contrast, we allow the fixed cost to be product/time specific in both estimation and counterfactual simulations (because smartphones in our data differ significantly in their quality), and obtain a less conclusive result for the welfare analyses of adding a product: the change in total welfare is positive when the fixed cost is not more than 2.3 times of its estimated lower bound. In other words, we are only able to quantify how small the fixed cost needs to be (relative to its lower bound) so that adding it increases welfare.[26] Therefore, there is a tradeoff between the benefit of less structure and the cost of a weaker result in our simulations of adding a product. In the merger simulations, we directly make assumptions on how far away the actual fixed cost may be from our estimated one-sided bound (and show robustness with respect to various alternative assumptions we make). Therefore, there is again a non-trivial tradeoff: on the one hand, we do not make the above assumptions about the structure of the fixed cost function; on the other hand, we need to make assumptions on the other bound and the distribution of the fixed cost within the bounds. In sum, our approach has an advantage in the welfare analysis where we drop products, while there is a non-trivial tradeoff between our approach and the existing ones for other analyses.

Both our approach and the existing ones assume that the total fixed cost of a firm is the sum of the fixed cost for each product. This means that we do not allow economies or diseconomies of scope in fixed costs, which is particularly problematic for the merger simulations because economies of scope may lead to an increase in product offering after the merger, the opposite of our result. To address this concern, we conduct a robustness analysis in Supplemental Appendix SA where we assume a parametric function of the fixed cost and estimate the degree of economies or diseconomies of scope in fixed costs following the moment inequality literature.[27]

In the merger simulations, we compute the equilibrium product portfolio of each firm. In such a discrete game, there is a concern of multiple equilibria. To address this concern, we use three different sequences in our best-response iteration. In the first two algorithms, we allow firms to take turns to update their best responses. The sequence is determined by their monthly sales in March 2013, either ascending or descending. In the last algorithm, we allow firms to update simultaneously in each round of the best-response iteration. The three algorithms lead to the same equilibrium. That said, we cannot rule out the possibility of multiple equilibria.[28] In contrast,

[26] It is unlikely that the fixed cost of the added products we consider (which are in the middle of the quality range) will be much larger than that of the offered products. For example, Samsung offers a large number of products of varying qualities between their low-end and high-end products (see Table 2). Adding a product in this quality range is, therefore, unlikely to be prohibitively costly.

[27] See, for example, Chernozhukov, Hong and Tamer (2007), Holmes (2011), Pakes, Porter, Ho and Ishii (2015) and Wollmann (2018).

[28] In a similar context, Lee and Pakes (2009) and Wollmann (2018) argue that one could consider a sequence of movements in the best-response iteration as part of the model structure.

Berry, Eizenberg and Waldfogel (2016) and Eizenberg (2014) enumerate possible equilibria and find all those consistent with their fixed cost bounds. This approach is infeasible in our context as the number of possible equilibria is the product of the number of each firm's possible product portfolios. As mentioned, just for the merged Samsung-LG alone, the number of possible product portfolio is 2^{36} ($\approx 6.9 \times 10^{10}$).

7 Conclusion

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

We conclude by highlighting a few caveats of the paper. First, our model is static. We have two pricing stages and a large action space for product choice. Therefore, estimating a dynamic model in our setting is intractable or would require us to give up some richness in describing the set of products available in the market and the set of potential products. As a result, similar to many papers in the endogenous product choice literature (e.g., Seim (2006), Fan (2013), Eizenberg (2014), Crawford, Shcherbakov and Shum (2018) and Berry, Eizenberg and Waldfogel (2016)), our paper uses a static model to describe consumer demand and firm behavior. On the supply side, this modeling choice is somewhat justifiable as we focus on non-flagship products in the baseline and such products presumably do not involve a large sunk cost such as the R&D cost (and we conduct robustness analyses by including flagship products). However, consumers may be dynamic, which will lead to firm dynamic behavior. For example, it may be costly for consumers to switch from one carrier to another. Given such frictions, firms may consider how their decisions in the current period affect their payoffs in the future. Note that, in a reduced-form way, our carrier/year fixed effects in the utility function capture an average switching cost.[29] Similarly, our estimated fixed cost in a reduced-form way captures both the true fixed cost and the effect of a product on future firm profits. That said, our static modeling choice rules out firms' forward-looking strategic behavior.

Second, our model does not explain the choice of carriers for each product by a smartphone firm. We could expand our definition of potential products for each firm to allow the firm to choose carriers. For example, we could define potential products for a firm as follows: (product j,

[29]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.

AT&T), (j, T-Mobile), ..., (j, AT&T and T-Mobile), ... However, given that doing so increases the computational burden substantially and that in the data, we do not observe smartphone firms moving products from one carrier to another, we leave this for future research.

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Appendices

A List of Flagship Smartphones

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

Flagship Products (2009/01 – 2013/03)

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

B Additional Merger Simulations

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

B.1 Merger Simulations with Different Specifications

We repeat the Samsung-LG merger simulation with four variations in this section. In the first variation, we use a different assumption on the post-merger brand effect for the merged firm. In the second variation, we use different ranges for the fixed cost draws. In the third variation, we allow firms to adjust flagship products as well as non-flagship products. In the fourth variation, we treat the coefficient of each product characteristic as an independent random coefficient.

B.1.1 Variation 1. Post-merger Brand Effect

As mentioned in Footnote 23, for the merger simulation in Section 5, we assign the Samsung brand effect to products originally offered by Samsung before the merger and the LG brand effect to those originally offered by LG. In this section, we repeat the merger simulation under the assumption that the post-merger Samsung-LG brand effect is the average of the pre-merger Samsung brand effect and the LG brand effect. The results in Table B.1 show that our main findings are robust to this new assumption.

Table B.1: Samsung-LG Simulation Results Using the Average Brand Effect for the Merged Firm

	Variable	Pre-merger	Post-merger	Change
(1)	Number of products	70	65.60	-4.40
(2)	merged firm	30	24.60	-5.40
(3)	non-merging firms	40	41.00	1.00
(4)	Variety	360.25	345.39	-14.85
(5)	Sales-weighted avg quality	8.50	8.54	0.04
(6)	merged firm	7.31	7.44	0.13
(7)	non-merging firms	6.23	6.23	0.0003
(8)	Sales-weighted avg price ($)	101.73	105.33	3.60
(9)	merged firm	151.04	173.71	22.67
(10)	non-merging firms	85.24	85.73	0.49
(11)	Total sales	7,205,974	7,067,759	-138,215
(12)	merged firm	1,805,421	1,574,917	-230,504
(13)	non-merging firms	5,400,553	5,492,842	92,288
(14)	Consumer surplus (million $)	1735.41	1693.82	-41.59
(15)	Carrier profit (million $)	1322.66	1293.56	-29.10
(16)	Smartphone firm profit (million $)	1184.26	1203.75	19.49
(17)	merged firm	214.37	214.67	0.30
(18)	non-merging firms	969.89	989.08	19.19

B.1.2 Variation 2. Fixed Costs

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

(1) $\left[\bar{F}_{jt} - (\bar{F} - \underline{F}), \bar{F}_{jt}\right]$ for a product in the data and $\left[\underline{F}_{jt}, \underline{F}_{jt} + (\bar{F} - \underline{F})\right]$ for a potential product not in the data, where $\bar{F} = 6.19$ and $\underline{F} = 5$ are, respectively, the average upper bound and the average lower bound reported in Section 4.

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

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

Table B.2: Samsung-LG Simulation Results Using Different Ranges for Fixed-cost Draws

Variable	Pre-merger	Post-merger	Change
Alternative Fixed-cost Range (1)			

(1)	Number of products	70	67.80	-2.20
(2)	merged firm	30	25.40	-4.60
(3)	non-merging firms	40	42.40	2.40
(4)	Variety	360.25	354.49	-5.76
(5)	Sales-weighted avg quality	8.50	8.51	0.01
(6)	merged firm	7.31	7.29	-0.02
(7)	non-merging firms	6.23	6.23	-0.003
(8)	Sales-weighted avg price ($)	101.73	101.22	-0.51
(9)	merged firm	151.04	157.39	6.35
(10)	non-merging firms	85.24	85.63	0.39
(11)	Total sales	7,205,974	7,077,437	-128,537
(12)	merged firm	1,805,421	1,537,816	-267,605
(13)	non-merging firms	5,400,553	5,539,621	139,068
(14)	Consumer surplus (million $)	1735.41	1690.72	-44.69
(15)	Carrier profit (million $)	1322.66	1295.02	-27.65
(16)	Smartphone firm profit (million $)	1151.42	1176.45	25.04
(17)	merged firm	196	199.5	3.50
(18)	non-merging firms	955.41	976.95	21.54
	Alternative Fixed-cost Range (2)			
(1)	Number of products	70	68.20	-1.80
(2)	merged firm	30	25	-5.00
(3)	non-merging firms	40	43.20	3.20
(4)	Variety	360.25	354.03	-6.21
(5)	Sales-weighted avg quality	8.50	8.50	0.01
(6)	merged firm	7.31	7.30	-0.01
(7)	non-merging firms	6.23	6.22	-0.01
(8)	Sales-weighted avg price ($)	101.73	100.71	-1.02
(9)	merged firm	151.04	157.9	6.86
(10)	non-merging firms	85.24	84.97	-0.27
(11)	Total sales	7,205,974	7,089,907	-116,067
(12)	merged firm	1,805,421	1,530,478	-274,943
(13)	non-merging firms	5,400,553	5,559,429	158,876
(14)	Consumer surplus (million $)	1735.41	1693.69	-41.72
(15)	Carrier profit (million $)	1322.66	1297.18	-25.49
(16)	Smartphone firm profit (million $)	1142.03	1166.66	24.63
(17)	merged firm	191.04	195.03	3.98
(18)	non-merging firms	950.98	971.63	20.65

B.1.3 Variation 3. Allowing for Adjusting Flagship Products

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

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

	Variable	Change	
		(1) Old Flagship Products Included	(2) All Flagship Products Included
(1)	Number of products	-2.80	-1.60
(2)	merged firm	-3.60	-3.00
(3)	non-merging firms	0.80	1.40
(4)	Variety	-22.32	-22.93
(5)	Sales-weighted avg quality	0.03	0.007
(6)	merged firm	0.03	-0.08
(7)	non-merging firms	0.0006	0.001
(8)	Sales-weighted avg price ($)	1.76	-1.94
(9)	merged firm	10.43	-4.35
(10)	non-merging firms	0.51	1.29
(11)	Total sales	-87,378	-138,445
(12)	merged firm	-144,064	-233,733
(13)	non-merging firms	56,686	95,288
(14)	Consumer surplus (million $)	-27.28	-47.30
(15)	Carrier profit (million $)	-16.08	-24.58
(16)	Smartphone firm profit (million $)	12.77	22.18
(17)	merged firm	1.42	1.77
(18)	non-merging firms	11.34	20.41

B.1.4 Variation 4. Independent Random Coefficients

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

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

In Section 5, we have shown the simulation result for a merger between Samsung and LG in March 2013, the second and third largest firms in terms of sales in that month. In this section, we conduct two additional merger simulations: a Samsung-Motorola merger (a merger between the second-largest and the fourth-largest firms) and an LG-Motorola merger (a merger between the third-largest and the fourth-largest firms). The simulation results are presented in Table B.5. A comparison of the results in Table 9 for the Samsung-LG merger to the results here shows that, not surprisingly, the merger effects on welfare are smaller for mergers between smaller firms. However, the qualitative findings are robust. Specifically, we find that all three mergers lead to a decrease in product variety. In terms of welfare, all three mergers result in a decrease in both consumer

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

	Variable	Pre-merger	Post-merger	Change
(1)	Number of products	70	67	-3
(2)	merged firm	30	25.80	-4.20
(3)	non-merging firms	40	41.20	1.20
(4)	Variety	94.83	94.83	-0.01
(5)	Sales-weighted avg quality	5.86	5.88	0.03
(6)	merged firm	5.07	5.10	0.03
(7)	non-merging firms	4.08	4.08	0.001
(8)	Sales-weighted avg price ($)	66.02	69.59	3.57
(9)	merged firm	55.14	63.49	8.34
(10)	non-merging firms	73.86	73.64	-0.22
(11)	Total sales	7,213,074	7,085,325	-127,750
(12)	merged firm	3,023,017	2,826,201	-196,817
(13)	non-merging firms	4,190,057	4,259,124	69,067
(14)	Consumer surplus (million $)	1515.07	1481.19	-33.88
(15)	Carrier profit (million $)	1265.04	1241.09	-23.95
(16)	Smartphone firm profit (million $)	1128.01	1139.99	11.98
(17)	merged firm	492.37	494.71	2.34
(18)	non-merging firms	635.63	645.28	9.65

and carrier surplus, but an increase in smartphone producer surplus. The overall welfare effect is always negative.

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

	Variable	Pre-merger	Post-merger	Change
	The Samsung-Motorola Merger			
(1)	Number of products	70	67.80	-2.20
(2)	merged firm	25	22.80	-2.20
(3)	non-merging firms	45	45	0
(4)	Variety	360.25	349.68	-10.57
(5)	Sales-weighted avg quality	8.50	8.51	0.01
(6)	merged firm	7.35	7.35	-0.001
(7)	non-merging firms	6.25	6.25	0.001
(8)	Sales-weighted avg price ($)	101.73	102.03	0.31
(9)	merged firm	161.91	166.48	4.57
(10)	non-merging firms	83.96	84.39	0.43
(11)	Total sales	7,205,974	7,139,091	-66,883
(12)	merged firm	1,642,828	1,534,471	-108,356
(13)	non-merging firms	5,563,146	5,604,620	41,473
(14)	Consumer surplus (million $)	1735.41	1713.4	-22.01
(15)	Carrier profit (million $)	1322.66	1306.51	-16.16
(16)	Smartphone firm profit (million $)	1184.26	1197.08	12.82
(17)	merged firm	206.72	208.58	1.86
(18)	non-merging firms	977.54	988.49	10.95
	The LG-Motorola Merger			
(1)	Number of products	70	69.40	-0.60
(2)	merged firm	19	18.40	-0.60
(3)	non-merging firms	51	51.00	0
(4)	Variety	360.25	357.14	-3.10
(5)	Sales-weighted avg quality	8.50	8.50	0.005
(6)	merged firm	7.18	7.17	-0.01
(7)	non-merging firms	6.42	6.42	0.0005
(8)	Sales-weighted avg price ($)	101.73	101.9	0.17
(9)	merged firm	132.56	134.43	1.87
(10)	non-merging firms	98.26	98.41	0.15
(11)	Total sales	7,205,974	7,186,545	-19,429
(12)	merged firm	727,812	693,794	-34,018
(13)	non-merging firms	6,478,162	6,492,751	14,589
(14)	Consumer surplus (million $)	1735.41	1729.05	-6.36
(15)	Carrier profit (million $)	1322.66	1318.07	-4.59
(16)	Smartphone firm profit (million $)	1184.26	1188.38	4.12
(17)	merged firm	54.11	54.26	0.14
(18)	non-merging firms	1130.15	1134.12	3.97