1.1 Introduction

Smartphone manufacturers generally produce a range of products covering many different quality levels. As an example, 28 companies operating in the US smartphone market unveiled 245 different models in the last quarter of 2018 alone. For just one company, Samsung, consumers could choose from a minimum of three models in every $100 price band.

Within the smartphone market, this proliferation of products is a result of the manufacturers' oligopolistic competition in the product space. From a social planner’s perspective, we must ask whether this competition causes a paucity or excess of products. This paper will examine this question from the perspective of the US smartphone market. The US has one of the most substantial smartphone markets globally, with over 260 million individuals using smartphones. Consonant with the global development of the smartphone market, smartphone user levels in the US have risen continuously over the last decade to today's level of over 80% coverage. Over the same period, sales revenue has also increased, with the market being worth $93 billion in 2018. The proliferation of new products is a significant feature of this market: for example, over the sampling period for this research, Samsung had an average of at least twenty-four smartphones on offer at any one time. Figure 1-1 shows the average number of smartphones offers by firms over time. This number is growing rapidly after 2015.

In theory, the existing oligopoly might lead to a paucity or excess of products, dependent on the market. Nevertheless, Spence (1976) notes that a number of different forces operate regarding product numbers and variety. Due to the setup costs, revenue may not be sufficient to meet costs, and so there will be a paucity of socially desirable products offered to the market. Conversely, however, Mankiw and Whinston (1986) note that companies do not take the business-stealing externalities into consideration, which may result in an excess of products.

In addition to the above, in the context of a multiple-product oligopoly, firms have to take into account the influence of cannibalization on their products. This influence tends to swing the overall equilibrium of numbers of products available towards paucity rather than excess. Looking at the complete picture, it is not totally clear how the above-mentioned factors will finally influence the market, i.e., whether competition leads to an excess of smartphone products. This is a question that must be answered empirically. This research will examine portfolio questions contextualized within the smartphone market in the US with the underlying objective of determining whether the existing oligopoly causes an excess or paucity of products, i.e., are there too many smartphones available, or too few?

To investigate the question, the research develops a structural model incorporating company decisions regarding products and pricing, and consumer demand. This model has been estimated based on data from the International Data Corporation (IDC). The available dataset supplies information regarding every smartphone product available in the US from the first quarter of 2010 to the fourth quarter of 2018. For all quarters across this time range, the research has observed the prices and quantities of smartphone sales for every model available in the US market. Additionally, the research has incorporated the most important specifications for all products, e.g., screen resolution, camera quality, battery life, storage capacity, type of processor, etc.

Using this data, the supply and demand model for smartphones has been estimated. The outcomes of this estimation are intuitive in that consumers are attracted by every smartphone characteristic apart from price: the average consumer wants larger screens, bigger phones, higher resolution displays, higher resolution cameras, and faster processors. These findings have been used to develop a product quality index representing a linear illustration of product characteristics with weighting supplied by the correspondent estimation of demand coefficient. This quality index is that employed for the construction of measurement of a variety of products. If a product is identical regarding its observable characteristics, its addition to the index will not influence the measure of variety, i.e., the variety measure will make a distinction between true differences in products and simple rebadging. The findings demonstrate that, throughout sampling, there was an increase in the range of products variety.

In terms of estimations of the supply side, a positive correlation was found between marginal costs and product quality. The upper and lower bounds for fixed costs were also revealed. This research is based on the assumption that a smartphone manufacturer's observable product portfolio maximizes profits in a Nash equilibrium. This means that the removal or addition of a product should not lead to increases in company profit. Based on this assumption, the study obtains upper bounds of fixed costs when I remove a product and lower bounds of fixed costs when a potential product that is not part of the dataset is included.

Based on the estimation of the parameters in coefficients, two sets of counterfactual simulations have been considered. With the first set, products are removed; with the second set, products are added. Prior to the fourth quarter of 2015, the findings demonstrate that the removal of a product leads to a decrease in total welfare for the majority of quarters. Subsequent to the fourth quarter of 2015, the removal of a product demonstrates an increase in total welfare in the majority of quarters. Such results held good no matter which product was removed. This result could be attributable to the fact that firms selling multiple products are incentivized to avoid cannibalizing their own product, which could drive equilibrium towards too few products in the market. However, if firms do not sufficiently consider business-stealing externalities, this could lead to being too many products in the market. The smartphone market has become more concentrated over time (see Figure 1-7). Prior to 2015, the average Herfindhal-Hirschmann Index stood at 1970; subsequent to 2015, it became 2796. When there is a moderate concentration in the smartphone market, companies are incentivized to avoid cannibalizing their own products, and this leads to too few products in the market. When higher levels of concentration are present in the market, companies have less concern regarding business-stealing externalities and are more preoccupied with deterring their competitors to avoid adding new products. This promotes a concentrated market; companies with market power will be more amenable to product addition when more competition is present. This may be attributable to the fact that loss from sales cannibalization is not as significant as the gains made if competitors can be deterred from product addition. In this case, this will result in too many products in the market.

For the second simulated set, a product has been added that fills a gap in the quality range. It is demonstrated that, in every instance, there is an increase in consumer surplus and variable profit increases for manufacturers. Prior to 2014, the majority of quarters show a positive variation in total surplus. This finding implies that the primary cause of this is that companies do not factor in consumer surplus increases when they take decisions, and this results in too few products in the market. Following 2014, even factoring in consumer surplus gains, the addition of a product will generally lead to negative fluctuations in total surplus. This finding offers confirmation of the fact that there were too many products on the market post-2015.

This research examines the welfare indications of product proliferation in the market in various stages of market development. It corresponds with a stream of research studying endogenous product choices. Ackerberg, Crawford, and Hahn (2011) and Crawford, Shcherbakov, and Shum (2011) have made contributions to the literature regarding companies' endogenous product selection. McManus (2010) revealed levels of quality distortion regarding "low quality" products in specialist coffee shops, which accorded with the predictions of nonlinear pricing modeling. In research that followed this, Berry and Waldfogel (2001) and Sweeting (2010) looked at the outcomes of relaxing limits on ownership in the US radio market as they correlated with the variety of products offered by companies. The first mentioned research revealed that the overall number of formats on offer, and the number per station, increased, increasing local radio market concentration. The second mentioned found that inside format parameters, stations with shared ownership designed playlists that offered greater differentiation from each other and made them more like their competitors.

In a marketplace in which the type of product offered by the company is discrete, decisions regarding the provision or otherwise of a product of similarities in both concept and method affect decisions to affect market entry. Because of this, previous researchers have added profitability conditions similar to those used in entry models to the standard framework in order to assess the fixed costs of introducing new products. Research using this technique includes that of Draganska, Mazzeo, and Seim (2009), Eizenberg (2011), and Sweeting (2011). Draganska et al. (2009) analyzed optimal product range and pricing choices regarding premium vanilla ice cream, Eizenberg (2011) looked at optimal Central Processing Unit (CPU) configuration and pricing for PCs, while Sweeting (2011) examined the optimal choices in terms of format for radio stations.

A number of researchers have endogenized both the number of products and product characteristics. Gandhi et al. (2008) undertook a numerical analysis of the ways products were repositioned following a merger (with fixed product numbers), Chu (2010) offered an analysis of the pricing and quality response to satellite TV from US cable television networks (with extant products), Fan (2010) made predictions of the way advertising prices were changing newspapers and the way a variety of continuous quality attributes would have been affected if contested mergers had gained approval, and Byrne (2011) undertook an analysis of the influences that mergers in the Canadian cable television market had on prices and quality.

In research nearer to the remit of this paper, Fan and Yang (2016) offered a wide-ranging examination of the influence on the welfare of competition and diversity of products within the smartphone sector. In their research, they revealed that higher levels of market concentration have a negative correlation with the variety of products manufacturers offer. However, employing more contemporary data, this research finds otherwise, i.e., that with a moderate concentration in the smartphone sector, there are too few products on the market; with a high concentration in the markets, there will be too many products.

The organization of this paper is hereby described: in Section 2, the data will be detailed; in Section 3, the empirical model will be described; in Section 4, the results will be presented; in Section 5, the estimates and recovered costs will be used to detail the counterfactual simulations, and the results will then be discussed.

1.2 Data

This research employs quarterly data regarding the US smartphone sales, prices of shipments, and characteristics of products supplied by IDC (2019). Aggregation of transaction data with product level has been undertaken over a nine-year period from the first quarter of 2010 to the fourth quarter of 2018, comprising 6748 unique product/market interactions. The unit sales on smartphones j have been divided by market size over the period t to derive the market share. The market size has been extracted from questionnaires regarding purchases of smartphones in the CES (Consumer Expenditure Survey). In the survey, approximately 10% of consumers were shown to purchase a new smartphone each quarter, making the non-purchase of a smartphone the outside option.

This research makes the assumption that all consumers are offered identical product specifications for the smartphone *j* and an identical price at that point in the market. Such an assumption may be made concerning product characteristics because smartphones do not undergo customization for the individual purchaser. However, the assumption that all consumers are offered the same price for the same smartphone appears to have a lower likelihood, given that cellphone providers offer their customers upfront subsidies if they purchase a service contract along with their smartphone. Nevertheless, it is reasonable to accept the argument of consumers that locked phones simply represent a discount in advance, which the service provider ultimately makes back over the lifetime of the service contract. The same reasoning holds good for the installment plans that are frequently offered to U.S. smartphone consumers.

Smartphone pricing was constructed from the IDC data regarding the average shipment price paid by retailers to manufacturers. Additional data regarding product characteristics were collected from www.PhoneArena.com and www.GMSArena.com.

Table 1-1 offers summary statistics regarding product prices, quantities, and characteristics of products. Smartphone markets have an average quarterly sale of approximately 186,610 units; the standard deviation for quarterly sales is approximately 4 times the mean. There are substantial variations in price over the course of the observations, with an average price of $264 and a standard deviation of $200. With every product, characteristics are observed, including build material, battery capacity, storage capacity, size, screen technology, the screen size (diagonal length), camera resolution, and processor. The standard deviations for such product characteristics are approximately 18%-220% of the correspondent means, demonstrating that the sample encompassed a considerable variety of products.

The sample encompasses 44 manufacturers and 1230 specific models of smartphones. In Table 1-2, we can see the 10 leading firms by average quarterly sale, these being Apple, Samsung, L.G. Electronics, ZTE, Motorola, HTC, Alcatel, BlackBerry, Google, and Kyocera. We can see from this table that Apple is the market leader, enjoying an average quarterly sale of 13.3 million units, with Samsung next with 8.32 million units. Every smartphone manufacturer in the sample offers multiple products at the same time: LG Electronics offers the highest number, with an average of 32 distinct products, with ZTE and Samsung next, offering an average of 27 products in a quarter.

Table 1-3 illustrates the variations of the multiple products offered by smartphone manufacturers in terms of price and characteristics. An average range and average standard deviation within- manufacturers /quarter dispersion is used to measure these elements. For an average range of characteristics; firstly, the maximum and minimum are calculated for every observation of a specific manufacturers-quarter combination. Following this, the average for such differences for every manufacturers-quarter combination within the sample is calculated. The second column reports the results for within- manufacturers/quarter dispersion. For average standard deviation, initially, the standard deviation for a variable for every observation for the same manufacturers/ quarter is calculated, e.g., the standard deviation for a manufacturer offering a single product will be 0, and then an average for standard deviation is calculated for every manufacturers/quarter in the sample.

From Table 1-3, within-manufacturers/ quarter standard deviation in price is $92.47. It is about half of the overall standard deviation of prices across the entire sample. This result indicates that within-manufacturers/ quarter variation main contributor of overall price variation. Note that the average within- manufacturers/quarter standard deviation for every variable is generally lower than the overall standard deviation for the total observations (Figure 1-1) but has significance. This implies that the within- manufacturers/quarter variation is a crucial contributor of the total variation.

1.2 Model

A. Demand Side

To address the research questions, this research commences with a specification of a random-coefficient logit (RCL) model of consumer demand within the differentiated product market. Let's assume that there are t=1, 2…, T markets, each having j=1, 2…, Jt products produced by f=1, 2…, Ft manufacturers, this provides a final figure of N products over all markets. There are i=1, 2…, It individuals/agents selecting from J_t products with an outside good j=0.

Indirect utility for agent i selecting product j in market t is

$$U_{ijt} = \delta_{jt} + \mu_{jti} + \epsilon_{ijt},$$

where

$$\delta = \underbrace{X_1^p \alpha + X_1^x \beta^x}_{X_1 \beta} + \xi.$$

The matrix X_1 holds the observed demand-side product linear characteristics, which may be segmented into the components: X_1^p and X_1^x. The X_1^p is $N \times K_1^p$submatrix of X_1 which holds endogenous characteristics. In this instance, $X_1^p = p$, price, and thus α is simply a scalar. The X_1^x

is $N \times K_1^x$ submatrix of X_1 which holds exogenous characteristics with $K_1^x \times 1$ is a vector of parameters β^x. Unobserved demand-side product characteristics, ξ, are a $N \times 1$ vector.

The agent-specific portion of utility is thus:

$$\mu = X_2(\Pi d' + \Sigma v').$$

This section of the specification incorporates both observable demographic and unobserved taste heterogeneity via random coefficients. d is a vector of consumers' observable characteristics, and the Π is $K_2 \times D$ matrix measuring the demographic variations in agent tastes. v represents unobservable taste characteristics, independently draws from the standard normal distribution. The Σ represents the Cholesky root in the covariance matrix for unobserved heterogeneous tastes.

Consumers then select from $J_t = \{0, 1, \dots, J_t\}$ discrete options, which includes the outside alternative ($u_{i0t} = 0$) and choose the alternative offering the highest level of utility:

$$decision_{jti} = \begin{cases} 1 & if\ U_{jti} > U_{kti} \quad \text{for all } k \neq j \\ 0 & otherwise \end{cases}$$

The aggregate market shares can be found through integration over the individual heterogeneous consumer choices distribution:

$$s_{jt}(\delta_{\cdot t}) = \int decision_{jti}\left(\delta_{\cdot t},\ \mu_{jti}\right) d\mu_{jti} d\epsilon_{jti}.$$

The error term ϵ_{jti} captures random idiosyncratic preferences which is assumed to be i.i.d and to follow Type I Extreme Value distribution. The aggregate market share for product j in market t is

$$s_{jti}(\delta_{\cdot t}, \theta_2) = \int \frac{e^{\delta_{jt}+\mu_{jti}}}{1 + \sum_{k=1}^{J_t} e^{\delta_{kt}+\mu_{kti}}} f\left(\mu_{jti} \middle| \theta_2\right) d\mu_{jti}$$

One is present in the denominator as there is a normalization of the mean utility of the outside good to $U_{0ti} = 0$. The $f(\mu_{jti}|\theta_2)$ represents the mixing distribution over the heterogenous types i and θ_2 parametrizes said heterogeneity. In fact, θ_2 holds all endogenous parameters for heterogeneous tastes. With a guess of θ_2, I solve the nonlinear equations system for the vector $\delta_{\cdot t}$ equating observed and predicted market share $S_{jt} = s_{jt}(\delta_{\cdot t}, \theta_2)$. With the $\delta_{\cdot t} = (S_t, \theta_2)$, x_{jt} , v_{jt}, p_{jt}, and ξ_{jt}, I can perform a linear instrumental variable (IV) generalized method of moments (GMM) regression of the form

$$\delta_{jt}(S_t, \theta_2) = \left[x_{jt}, v_{jt}\right]\beta - \alpha p_{jt} + \xi_{jt}$$

I construct the demand moments through the interaction of the predicted residuals $\hat{\xi}_{jt}(\theta_2)$ and demand-side instruments Z_{jt}^D forming

$$\Sigma_{jt}\hat{\xi}_{jt}(\theta_2)Z_{jt}^D,$$

with adding certain instruments Z_{jt}^D. The Z_{jt}^D is a $R \times 1$ vector of instruments with $R - K > 0$ excluded instruments correlate with price but uncorrelation with the structural error term. The supply-side section (below) employs the estimated demand parameters for calculating the vector of product market shares in every period, and also the matrix for share price derivatives.

B. Supply Side

A static Bertrand game is employed for describing the supply side. Consider the profits of firm f which for a market *t* controls several products J_f and sets prices p_{jt}, that is

$$\underset{p_{jt}:j_t \in J_f}{\arg\max} \sum\nolimits_{j_t \in J_f} (p_{jt} - c_{jt}) \cdot s_{jt}(\boldsymbol{p}, \boldsymbol{X}; \theta_2).$$

With the corresponding multiproduct differentiated Bertrand first-order condition being,

$$s_{jt}(\boldsymbol{p}, \boldsymbol{X}; \theta_2) \ + \sum_{k \in J_f} \frac{\partial s_{kt}}{\partial p_{jt}} (\boldsymbol{p}, \boldsymbol{X}; \theta_2)(p_{kt} - c_{kt}) = 0.$$

Rewrite this in vector-matrix form,

$$s_j(\boldsymbol{p}, \boldsymbol{X}; \theta_2) = \ \Delta \cdot (p - c) \text{ and}$$

$$\eta_{jt} \ = \ p - \ c \ = \ \underbrace{\Delta^{-1} s_j(\boldsymbol{p}, \boldsymbol{X}; \theta_2)}_{markups}.$$

With Δ is being as a matrix of own and cross-price share derivatives having the element-wise product of ownership matrix O, and elements $\partial s_j / \partial p_j$, given by

$$\Delta = \ -O \odot \frac{\partial s_j(\boldsymbol{p}, \boldsymbol{X}; \theta_2)}{\partial p_j}.$$

With O equals 1 if products produced by same manufacturer, otherwise equals 0. c represents the vector of marginal cost, p that of prices, and s_j that of market share. With the demand side of estimation, I can recovery of marginal costs for all the models on the basis of the firm's first-order conditions to maximize profits. Additionally, the first-order condition can also be employed for a simulation of a new equilibrium price in a counterfactual scenario. Firms have marginal cost functions that are log-linear in a vector of K_3 cost characteristics. Generally, we may parametrize marginal costs as:

$$log\big(p_{jt} - \ \eta_{jt}(\theta_2)\big) = log\big(c_{jt}\big) = \ X_{jt}\gamma_{jt} + \ \omega_{jt}.$$

As per the demand side, the cost characteristics are partitioned into observed and unobserved components. Observed supply-side product characteristics are located in the $N \times K_{jt}$ matrix X_{jt} and the γ contain supply-side parameters. ω_{jt} is $N \times 1$ vector containing unobserved supply product characteristics. The imposition of a functional form restriction on marginal cost c_{jt}, which is dependent on product characteristics X_{jt}, allows for recovery of the marginal cost. As the sales of smartphones within the US are frequently lower than the total number of units produced, as a result of international trading, and because it is not easy to obtain data regarding the product level of smartphones production, smartphone sales have been used to stand in for production. ω_{jt} represents an error term that could incorporate production costs resulting from unobserved product attributes and also any productivity shock. Endogeneity difficulties are caused by having to estimate non-constant marginal cost functions when we consider that there is a correlation between sales and unobserved product attributes. An assumption is made that unobserved product attributes have no mean dependency on unobserved product attributes. Using this assumption, we can derive instruments for smartphone sales using the observed attributes of products that compete with each other. I can construct the supply moment through the interaction of the predicted residuals $\widehat{\omega}_{jt}(\theta_2)$ and demand-side instruments Z_{jt}^S to create

$$\overline{g}_S(\theta_2) = \frac{1}{N}\Sigma_{jt}\widehat{\omega}_{jt}(\theta_2)Z_{jt}^S.$$

C. Decision on Products

An assumption is made that the ultimate product decisions are made by smartphone manufacturers; it is suggested by the Nash equilibrium that if the product portfolios of a competitor are at the equilibrium, deviation from the equilibrium product portfolio will not cause expected profits to rise to the manufacturer. Let's examine two forms of deviation, firstly the removal of a product from the sample, and secondly the addition of a product that is not in the dataset.

In the first instance (removal of a product from the sample), the manufacturer *f* 's expected profit should not rise with the removal of the product j_t from its portfolio.

$$E\pi_{ft} - F_{jt} \;\geq\; E\pi_{ft}^{without\ j_t}$$

With π_{ft} being the equilibrium variable profit for the smartphone manufacturer *f*, with F_{jt} being the fixed cost. $\pi_{ft}^{without\ j}$ represents the variable profit for manufacturer *f* when the model j_t is taken out of its product portfolio. Such an inequality provides an upper bound for the fixed cost of F_{jt} for j_t in the sample. With products on offer to the market, the fixed costs should be bounded from above.

The second case to be considered is one in which a potential product not contained in the dataset is added. The manufacturer *f* 's predicted profit should not increase when the potential product $\tilde{j}_t$ is added to its portfolio. The inequality below provides a lower bound for fixed costs for the potential product.

$$E\pi_{ft} \;\geq\; E\pi_{ft}^{with\ \tilde{j}_t} - F_{\tilde{j}_t}$$

It should be noted that $\tilde{j}_t$ does not form part of the product portfolio of the manufacturer *f*. $F_{\tilde{j}_t}$ should be bounded from below. This may be logically inferred as the fixed cost of a product not offered to market ought to should be bounded from below, e.g., the potential product under consideration is the one that has been discontinued.

1.4 Estimation

The generalized method of moments (GMM) challenge is

$$\hat{\theta} = \arg\min_{\theta} \underbrace{\bar{g}(\theta)'W\bar{g}(\theta)}_{GMM\ objective}.$$

Where W represents a $M \times M$ weighting matrix. The two sets of moments entering the GMM objective function are $g_D(\theta)$, the demand side moments, $g_S(\theta)$, and the supply side moments. Furthermore, θ may be partitioned into three segments: θ_1 containing the demand parameters β, θ_3 containing the supply parameters γ, and θ_2 containing the remaining parameters, including the α. Parameters $[\hat{\theta}_1(\theta_2), \hat{\theta}_3(\theta_2)]$ are implicit functions of θ_2, and so only θ_2 requires a nonlinear search.

$$\bar{g}(\theta_2) = \begin{bmatrix} \bar{g}_D(\theta_2) \\ \bar{g}_S(\theta_2) \end{bmatrix} = 0$$

To be explicit, the program runs in the following manner:

Step 1: For every guess for θ_2, the model's share predictions are matched with the ones in the data, i.e., I need to solve $S_{jt} = s_{jt}(\delta_{\cdot t}, \theta_2)$ for $\hat{\delta}_{\cdot t}(S_{jt}, \theta_2)$.

Step 2: Employ $\hat{\delta}_{\cdot t}(\theta_2)$ for recovery of the markup $\hat{\eta}_{\cdot t}(\theta_2) = \Delta_t(\hat{\delta}_{\cdot t}(\theta_2), \theta_2)^{-1}\boldsymbol{s_t}$

Step 3: Employing linear IV-GMM and the formulations below for recovery of $[\hat{\theta}_1(\theta_2), \hat{\theta}_3(\theta_2)]$.

$$\hat{\delta}_{jt}(S_t, \theta_2) + \alpha p_{jt} = [x_{jt}, v_{jt}]\beta + \xi_{jt}$$

$$log\big(p_{jt} - \hat{\eta}_{jt}(\theta_2)\big) = log\big(c_{jt}\big) = x_{jt}\gamma_{jt} + \omega_{jt}.$$

Step 4: The sample moments are stacked:

$$\bar{g}(\theta_2) = \begin{bmatrix} \frac{1}{N}\Sigma_{jt}\hat{\xi}_{jt}(\theta_2)Z_{jt}^{D} \\ \frac{1}{N}\Sigma_{jt}\widehat{\omega}_{jt}(\theta_2)Z_{jt}^{S} \end{bmatrix}$$

Step 5: The GMM problem is solved:

$$\hat{\theta} = \arg\min_{\theta} \bar{g}(\theta)' W \bar{g}(\theta).$$

A. Estimation procedure

The way in which marginal costs and demands are estimated is similar to that used by Berry, Levinsohn, and Pakes (1995). The demand and supply-side moments have been constructed, and the parameters estimated, employing the GMM. As a result of the collinearity associated with time-fixed effects, standard BLP instruments are not adequate tools for the identification of consumer demand. In order to mitigate this issue, the differentiation instruments were constructed following the recommendations of Gandhi and Houde (2017). As an example, a product *j* with characteristics x_{jt}, would produce a differentiation instrument:

$$z_{jt} = [x_{jt}, {z_{jt}}^{non-rival}(x_{jt}), {z_{jt}}^{Rival}(x_{jt})],$$

in which ${z_{jt}}^{non-rival}(x_{jt})$ is a matrix that consists of sums over functions of differences between non-rival goods, and ${z_{jt}}^{Rival}(x_{jt})$ is a matrix that consists of sums functions of differences over rival goods. Let x_{jtl} be characteristic l in X for product *j* in market *t*, which is produced by firm *f*. That is, $j \in j_{ft}$. Then,

$$ {z_{jtl}}^{non-rival}(\mathrm{X}) = \sum_{k,j \in J_t \; and \; k \neq j} (|d_{jktl}| < SD_l)$$

$$z_{jtl}{}^{rival}(\mathrm{X}) = \sum_{k \notin J_t} (|d_{jktl}| < SD_l)$$

in which $d_{jktl} = x_{ktl} - x_{jtl}$ represents the differences of products *j* and *k* regarding *l*, SD_l represents the standard deviation in pairwise differences calculated for every product in the markets *t* for characteristic *l*. Therefore, $|d_{jktl}| < SD_l$ shows that products *j* and *k* are quite similar in terms of characteristic *l*. The intuitive outcome from these instruments is that product demand is most frequently influenced by a low number of other products that share many similar features.

Identifying the demand parameters within consumer utility can be achieved by examining variations in consumer choice in the various options offered by manufacturers. The central assumption is that cost shifters are exogenous to consumer preference and that the characteristics of products contained in the choice are exogenous to unobserved demand shocks. It is generally argued, regarding differentiation instruments, that manufacturers decide upon the characteristics of their products prior to undertaking observation of demand shocks.

I can continue with GMM via an interaction of the error term and the vector of instrumental variables z_{jt} that does not correlate with the error term. Assume there are *K* mean valuation β_k, *K* standard deviations σ_k, with the price parameter α. It will require a minimum of *2K + 1* instruments in z_{jt}. Price p_{jt} is not a suitable instrument for the identification of price effects as it will generally have a correlation with unobserved demand-side characteristics of products. An example of this would be that a positive demand shock for the product *j* in market *t* will cause increases in product demand but may encourage the manufacturers to increase prices. Failure to take this endogeneity issue into account, the estimation will create an estimated price coefficient α that has a downward bias. As with BLP-type instruments, differentiation instruments are employed for the estimation of the *2K + 1* parameters. To be more specific, the vector of instrumental variables z_{jt} incorporates: a) the product characteristic vector x_{jt}; b) the sum over functions of differences between products produced by the same manufacturers; c) the sum over functions of differences between products from competing manufacturers.

Alongside the instruments mentioned above, several cost shifters have been included within the estimates, e.g., the weight of the device, 64-bit computing, and technology used to fabricate the processor (e.g., 14 nm). The market size used in the estimation is from the CES. In the CES, approximately 10% of consumers purchased a new smartphone each quarter. This model can also control for time fixed effects, processor vendor, and systematic brand effects.

B. Estimation Results

Table 1-4 illustrates the demand-side estimation results. The demand estimation results demonstrate that consumers are positively influenced by every characteristic of a smartphone apart from price. It can be seen that, in general, consumers have a preference for products with larger screens, larger dimensions, higher resolution displays, higher resolution cameras, and superior processing units. Specifically, the average consumer is willing to pay an extra $20.42 for a smartphone that uses LTE technology, $26.43 for an OLED screen in preference to a TFT screen, $28.09 for each additional megapixel in the selfie camera, $27.28 for each additional gigabyte of storage, $45 for higher level of display resolution, and $39.28 for each extra megahertz of CPU clock speed. Additionally, estimated standard deviations for consumer preferences in smartphone characteristics have significance and are near the average taste, implying that there is heterogeneity in the consumer willingness to pay more for improved features on their smartphones.

Table 1-6 illustrates own and cross-price elasticity with the ten most popular products (Apple iPhone 8, Apple iPhone 8 Plus, Apple iPhone X, Apple iPhone X.S., L.G. Aristo 2, Motorola E5 Play, Samsung Note 9, Samsung S9, and Samsung S9+) for the last quarter of 2018. It can be seen with the Apple iPhone 8+ that when the price increased by $10, demand fell by around 7.1%. Again, own-price elasticity has greater significance than cross-product price elasticity.

Figure 1-2 illustrates the way in which the quality of smartphones has evolved over time. Estimated parameters have been employed for the calculation of a product quality index, which linearly combined product characteristics with weighting supplied by corresponding estimated demand coefficients. This figure is constructed by plotting the median and maximum quality index for every product in every quarter. Maximum of quality index for Apple, Samsung, and LG has been added. The figure also shows that Samsung is almost the leading brand to drive the quality frontier. Apple was producing median quality product until Q1 2014, and higher quality product after that. The figure also demonstrates that LG, Samsung, and Apple are moving away from the medium quality. Apple has closed the gap in quality between iPhones and Samsung's galaxy products from Q2 2016 onwards.

Figure 1-3 demonstrates that the number of smartphones also increases over time. In the first quarter of 2010, there were 72 smartphones on offer to the market; by end of 2018, there were 244. Nevertheless, a rise in the number of smartphones does not necessarily match a rise in the variety of products. When manufacturers produce new products that can only be distinguished from extant ones in terms of minor features, e.g., color or name, this does not represent a contribution to variety in products. Product variety measurements were designed to illustrate the way in which product variety has evolved over time. To be specific, we can measure product variety in a market containing *n* products using:

$$\left[\sum_{k=2}^{n} \sqrt{(q^{k} - q^{k-1})}\right]^{2}.$$

In which $q^1 < \cdots < q^n$ represent the qualities of *n* products (ascending order). This measurement of the product variety is desirable, because adding identical quality products do not influence the measurement of product variety. Figure 1-4 illustrates the way product variety measures increase over time. This product variety measure is a simple way of capturing product variety and distinguish the meaningful product from the obfuscate product. However, product variety cannot directly speak for welfare, consumer surplus might not be monotonic with it.

Results from the regression of estimated marginal costs on the smartphone characteristics are showed in Table 1-5. Most of the smartphone characteristics are significant and have the expected sign. It cost more to make smartphone with better graphic benchmarks, higher resolution of cameras, larger storage, higher resolution, NFC, bigger battery, water resistant, OLED screen, and so on. Marginal costs also increase in product quality. Fixed cost bounds have been computed on the basis of estimating marginal costs and demand. As above, upper bounds can be obtained for every product within the dataset, and lower bounds for any product not in the dataset. Figure 1-5a shows the plots for the upper bound of fixed cost, while Figure 1-5b shows the plots for the lower bound of fixed cost for products that are no longer available. The horizontal axis represents product qualities, and the vertical axis represents fixed cost bounds. These two figures imply a positive correlation between fixed cost and the quality of the product. In Figure 1-5a, the average upper bound is \$23.51M; Figure 1-5b shows the average lower bound as \$9.09M.

1.5 Counterfactual Simulations

This section will run counterfactual simulations in addressing the research question, "Are there too few or too many products in the market?" This question is addressed initially by running a counterfactual simulation in which a product is removed from the market. The product with the lowest quality is removed from the market for every quarter from 2010-2018; the new pricing equilibrium is calculated for every simulation draw with the correspondent consumer and producer surpluses being calculated, with an average than being taken over every draw. Following this, the counterfactual simulation is repeated with the removal of median quality and then highest quality products. The outcomes of these exercises can be seen in Tables 1-7a, 1-7b, and 1-7c. Each of the tables illustrates a simulation with the removal of different types of products, e.g., in Table 1-7a columns two and three, I report the change in consumer surplus and change in the sum of the variable profits for smartphone manufacturers. The fourth column illustrates the upper bound for the fixed cost of the product that has been removed, which represents the highest saving that can be achieved in the fixed cost. In column five, I report the overall welfare change caused by the removal of the lowest quality product. The final column illustrates which company's product has been removed.

The findings from these three tables (Table 1-7a. 1-7b, and 1-7c) demonstrate that consumers suffer from product removal, e.g., in the last quarter of 2018, consumer surplus falls by $1.37 million in the lowest quality product removal scenario, $5.32 million in the medium quality product removal scenario, and $15.04 million in the highest quality product removal scenario. Revenue generation for these products in this quarter is shown to be $26 million, $72 million, and $153 million, respectively. This is roughly 10 to 20 times more than consumer surplus lose from removing relative products. This is partially due to change in prices after products are removed. More important contribution to falls in consumer welfare is direct effect of product removal. If the product prices are assumed to be unchanged, consumer surplus changes by $1.1 million, $4.48 million, and $13.73 million for the respective qualities, and this accounts for the majority of the overall variation in consumer surplus.

For smartphone manufacturers, comparing the third and fourth columns in all three tables (Table 1-7a. 1-7b, and 1-7c) demonstrates that when the fixed costs are at their upper bound, there will be an increase in overall smartphone producer surplus following the removal of a product. This finding confirms the intuitive belief that as manufacturers are not internalizing the business-stealing effect, the equilibrium may be driven in the direction of having too many products in the market. Nonetheless, this effect is dominated by the effect of change in consumer surplus before 2015. A summation of the change in consumer surplus, producer surplus, and the greatest possible savings of fixed costs shows a decrease in total welfare before 2015. There are too few products in the market before 2015. After 2015, saving in fixed costs start to dominate business-stealing effect, total welfare becomes positive in most of the case when the product is removed. There are too many products in the market after 2015.

Comparison of the findings from Table 1-7a, 1-7b, and 1-7c shows that changes in the magnitude of welfare measure increase as I switch from the removal of the lowest quality product to the removal of the highest quality product (also see Figure 1-6). The most significant conclusion does not vary for any quality group. When the exercise is repeated for different products for each quarter, it is shown that the results remain consistent across every simulation. There will always be negative changes in consumer surplus and the variable profits of the smartphone manufacturers.

In summary, before 2015, the findings demonstrate that the removal of products leads to a fall in total welfare in the majority of quarters. After 2015, when a product is removed from the market, the outcomes of the simulation demonstrate a positive change in total welfare in the majority of quarters. These findings hold good regardless of which product is removed. This result may be attributable to the fact that firms offering multiple products are incentivized to avoid cannibalizing their existing products, and so the equilibrium may be driven towards too few products. However, if firms do not account for business-stealing externalities, excessive product proliferation may result. Before 2015, the maximum number of products available in the smartphone market was approximately 139. After 2015, well over 300 different products were on offer. Market competitiveness also shows fluctuations over time. Figure 1-9 illustrates the calculation for the Herfindahl-Hirschman Index (HHI) over time. Prior to 2015, the average HHI was 1970; subsequently, it is 2796. With a moderate concentration in the smartphone market, firms are incentivized not to allow cannibalization of their products, and so there are too few products on the market. When the market reaches a high level of concentration, firms are less likely concerned with business-stealing externalities, having a greater concern with deterring their competitors from adding new products. This results in a concentrated market, with firms that have market power being incentivized to introducing new products to the existing offering in this more competitive market. This may be due to the fact that any losses caused by cannibalization are lower than the gains accrued from deterring competitors from introducing new products. In this scenario, there will be too many products in the market.

We must now consider whether the addition of a product causes increases in welfare. We shall look at the addition of a product that fits into a gap in the quality spectrum. An example can be found in Figure 1-7, where a partial plot for product quality in the last quarter of 2018 shows that the widest gap in the quality index exists between 3.67 and 3.79, and so I can add a product of a quality level in the midpoint of this interval. Simulations were undertaken in which products of Apple, Samsung, and LG were added. Table 1-8 presents the results of these simulations.

Consumers benefit when a product is added to the market (see Table 1-8). The total variable profit for smartphone manufacturers also rises. A lower bound of fixed costs for the additional product was estimated; this is always greater than the fluctuations in the total variable profits for the manufacturer. There is a negative difference between the variable costs of the manufacturer and the lower bond of fixed costs, demonstrating that total profit for a manufacturer falls with the addition of a product.

Before 2014, the change in total surplus appears positive in the majority of quarters. These findings appear to indicate that this is primarily due to the fact the manufacturers do not factor in increases in consumer surplus in their decision-making processes, and thus the market has too few products. After 2014, even when increases in consumer surplus are considered, the addition of a product, in the majority of instances, results in a negative change in total surplus. These findings also confirmed that there were too many products in the market after 2015.

In summary, the reulst of simulations that add or remove products indicate that there are too few products when the market is not concentrated. With a greater concentration in the market, the market starts to show the signs of too many products. There are three reasons that product proliferation is inefficient in the market of smartphones: first, manufacturers offering multiple products attempt to avoid cannibalization by restricting their product offering. Second, manufacturers that disregard cannibalization will generally offer more products. Third, companies do not take consumer surplus into consideration, which causes insufficient product offerings.

1.6 Conclusion

This research has studied the way in which product proliferation in the smartphone market in the US is impacted by oligopolistic competition. To achieve this, a model was developed to estimate the demand and supply of smartphones. Counterfactual simulations have been undertaken with products being removed or added in order to determine whether there are too few or too many products in the market. The results suggest that there are too few products in the market when it is at a less concentrated level, and too many products as the market becomes more concentrated. With a moderate level of concentration in the market, firms are incentivized not to cannibalize their products, and firms do not take into account the increase in consumer surplus when making decisions, markets result in too few products. As the market becomes highly concentrated, firms care less about business-stealing externality, the market results in too many products.

The primary limitation of this research is the static model employed; as with much research in the area of endogenous product choice, a static model is employed for describing firms' behaviors and consumer demand. For the supply side, this modeling choice is somewhat justifiable as I focus on median-quality or low-quality product choices. However, for high-quality products that require a sizable R&D cost, it could be problematic. Consumers can be dynamic, which also leads to firms behave dynamically; e.g., consumers may find it prohibitively expensive to change platforms. These dynamics may encourage firms to consider the way contemporary choices may influence their future profits. I have a large number of product choices in the dataset. Therefore, the trade-off of estimating a dynamic model would be intractable and it would give up richness in product availability in the market and sets of potential products. Implementing dynamic demand estimation is challenging and is left for future research.

Table 1-1: Summary Statistics

Variable	Mean	S. D	Min	Max
Sales (1000)	186.61	697.33	1	13400
Prices (2010USD)	264.93	199.71	11	1295
Processing units				
Core	3.69	2.32	1	10
Speed (mhz)	1411	498	225	2842
Graphics	79.89	181.37	0.5	1853
Technology(nm)	33.57	18.28	7	130
Ram (gb)	1.51	1.23	0.001	10
Camera				
Rear Camera (mp)	8.46	4.75	0	41
Selfie Camera (mp)	2.96	3.28	0	24
Dimensions				
Length	5.29	0.77	2.44	7.08
Width	2.82	0.59	1.93	6.5
Depth	0.39	0.09	0.2	0.82
Weight(oz)	5.27	0.95	3.1	11.82
Display Specs				
Screen Size (inch)	4.64	0.9	2.2	6.46
Display Resolution	1395	674	181	4405
OLED	0.16	0.37	0	1
IPS	0.16	0.37	0	1
Glass Screen	0.44	0.49	0	1
Storage Size (gb)	17.58	24.34	0.1	275.23
Battery Size (mha)	2340	837	900	9000
Metal Body	0.15	0.36	0	1

Table 1-2: Top Ten Smartphone Manufacturers

Firm	Average quarterly sales (million units)	The average number of products
Apple	13.30	6
Samsung	8.32	27
LG Electronics	3.98	32
ZTE	2.24	27
Motorola	1.73	13
HTC	1.37	12
Alcatel	1.10	22
BlackBerry	1.00	11
Google	0.78	3
Kyocera	0.50	7

Table 1-3: Product Characteristics Dispersion Within a Manufacturer/Quarter

Variable	Average range[a]	Average S. D[b]
Prices (2010USD)	288.42	92.47
Processing units		
Core	2.28	0.85
Speed (mhz)	650.24	218.37
Graphics	157.34	52.82
Technology(nm)	15.78	0.25
Ram (gb)	1.32	0.44
Camera		
Rear Camera (mp)	6.08	2.10
Selfie Camera (mp)	3.49	1.16
Dimensions		
Length	1.12	0.35
Width	0.76	0.24
Depth	0.10	0.03
Weight(oz)	1.68	0.54
Display Specs		
Screen Size (inch)	1.11	0.36
Display Resolution	143.58	47.04
Storage Size (gb)	27.21	8.59
Battery Size (mha)	1042.14	332.80

a. First, I compute the range of a variable (the difference between the maximum and the minimum among all observations) for a given manufacturer/quarter. Then take the average of these ranges across all manufacturers.
b. First, I compute the standard deviation across all observations in the same manufacturer/quarter. Then I take the average of standard deviations across manufacturer/quarter in the sample. Note that the standard deviation of the manufacturer with only one product will be 0.

Table 1-4: Demand Side Estimation Results

	Mean		Standard deviations	
Variable	Parameter	s.e	Parameter	s.e
Prices	-0.021	0.005	-	-
Price/income	-	-	-0.107	0.383
Processing units				
Core	0.789	0.080	0.125	0.071
Speed (mhz)	0.825	0.092	0.138	0.072
Graphics	0.432	0.156	0.152	0.146
Ram (gb)	0.086	0.151	0.161	0.138
Rear Camera (mp)	0.676	0.145	0.168	0.146
Selfie Camera (mp)	0.590	0.086	0.178	0.079
Storage Size (gb)	0.573	0.232	1.200	0.032
Screen Size (inch)	0.765	0.086	0.100	0.090
Display Resolution	0.945	0.111	0.109	0.129
Length	0.048	0.119	0.121	0.095
Width	0.424	0.158	0.125	0.161
Depth	0.691	0.163	0.140	0.140
Battery Size	0.405	0.164	0.149	0.192
Metal Body	0.600	0.165	0.154	0.142
NFC	0.456	0.113	0.152	0.095
Water Resistant	0.619	0.092	0.174	0.064
Glass Screen	0.603	0.079	0.153	0.065
OLED	0.555	0.093	0.195	0.053
IPS	0.197	0.079	0.185	0.051
LTE	0.429	0.051	0.204	0.032
GPS Chips	0.181	0.055	0.216	0.033
Fixed Effects				
Year			Yes	
Quarter			Yes	
Brand			Yes	

Table 1-5: Supply Side Estimation Results

Variable	Parameter	s.e
Processing units		
Core	-0.027	0.008
Speed (mhz)	-0.108	0.020
Graphics	0.143	0.011
Ram (gb)	-0.021	0.013
Fabrication (nm)	-0.176	0.016
64-Bit	0.004	0.014
Rear Camera (mp)	0.323	0.020
Selfie Camera (mp)	0.012	0.006
Storage Size (gb)	0.164	0.010
Screen Size (inch)	-0.231	0.022
Display Resolution	0.292	0.025
Length	0.098	0.015
Width	-0.001	0.018
Depth	-0.023	0.014
Battery Size	0.091	0.016
Metal Body	0.096	0.015
NFC	0.162	0.014
Water Resistant	0.122	0.019
Glass Screen	0.072	0.011
OLED	0.115	0.017
IPS	-0.014	0.015
LTE	0.066	0.014
Weight	-0.097	0.014
GPS Chips	0.222	0.018
Fixed Effects		
Year	Yes	
Brand	Yes	
Processor Vendors	Yes	

Table 1-5: Top Ten Products of Own- and Cross-price Elasticities (2018q4)

	Apple iPhone 8 (1)	Apple iPhone 8+ (2)	Apple iPhone X (3)	Apple iPhone XS (4)	iPhone XS Max (5)	LG Aristo 2 (6)	Moto E5 Play (7)	Samsung Galaxy Note9 (8)	Samsung Galaxy S9 (9)	Samsung Galaxy S9+ (10)
(1)	-6.028	0.533	0.530	0.584	0.388	0.015	0.014	0.400	0.261	0.258
(2)	0.530	**-7.152**	0.640	0.618	0.538	0.021	0.020	0.569	0.356	0.392
(3)	0.389	0.473	-5.639	0.573	0.499	0.008	0.008	0.501	0.252	0.314
(4)	0.299	0.318	0.400	-3.753	0.074	0.004	0.003	0.371	0.150	0.194
(5)	0.168	0.234	0.293	0.062	-2.821	0.002	0.002	0.310	0.122	0.186
(6)	0.109	0.157	0.082	0.051	0.042	-5.060	0.161	0.081	0.146	0.111
(7)	0.088	0.131	0.066	0.039	0.033	0.142	-4.978	0.069	0.129	0.097
(8)	0.305	0.436	0.520	0.551	0.546	0.008	0.008	-5.597	0.248	0.368
(9)	0.464	0.637	0.609	0.520	0.503	0.036	0.036	0.579	-8.128	0.468
(10)	0.410	0.626	0.679	0.603	0.683	0.024	0.024	0.767	0.418	-7.997

Table 1-7a: Change of Welfare When Lowest Quality Products are Removed (Million $)

Year	ΔCS	ΔPS	FC	**ΔW**	Firm
2010Q1	-0.36	-0.31	0.34	**-0.34**	BlackBerry
2010Q2	-0.35	-0.55	0.67	**-0.23**	BlackBerry
2010Q3	-0.54	-0.69	0.74	**-0.49**	BlackBerry
2010Q4	-0.67	-0.55	0.88	**-0.34**	BlackBerry
2011Q1	-0.71	-0.72	1.13	**-0.29**	BlackBerry
2011Q2	-0.88	-0.67	1.23	**-0.32**	BlackBerry
2011Q3	-0.79	-0.48	1.25	**-0.03**	BlackBerry
2011Q4	-1.76	-1.10	1.29	**-1.58**	BlackBerry
2012Q1	-1.48	-0.95	1.51	**-0.93**	BlackBerry
2012Q2	-1.09	-0.95	1.58	**-0.46**	BlackBerry
2012Q3	-0.99	-0.80	1.67	**-0.13**	BlackBerry
2012Q4	-1.35	-1.25	1.92	**-0.69**	BlackBerry
2013Q1	-1.08	-0.89	1.96	**0.00**	BlackBerry
2013Q2	-1.16	-1.19	2.03	**-0.32**	BlackBerry
2013Q3	-1.54	-0.84	2.07	**-0.31**	BlackBerry
2013Q4	-2.07	-1.13	2.33	**-0.87**	BlackBerry
2014Q1	-1.56	-1.05	2.45	**-0.15**	BlackBerry
2014Q2	-1.07	-1.01	2.64	**0.57**	BlackBerry
2014Q3	-1.33	-1.01	2.89	**0.55**	BlackBerry
2014Q4	-1.99	-1.34	3.19	**-0.15**	BlackBerry
2015Q1	-1.81	-0.97	3.60	**0.82**	Huawei
2015Q2	-0.83	-0.97	3.69	**1.89**	Huawei
2015Q3	-1.81	-1.27	3.79	**0.70**	Huawei
2015Q4	-1.98	-1.58	3.84	**0.28**	Huawei
2016Q1	-1.64	-1.25	3.08	**0.19**	Samsung
2016Q2	-1.35	-0.72	3.45	**1.38**	Samsung
2016Q3	-1.63	-1.11	3.54	**0.80**	Samsung
2016Q4	-3.21	-2.63	3.92	**-1.93**	Samsung
2017Q1	-1.96	-0.79	3.98	**1.24**	ZTE
2017Q2	-1.16	-1.57	3.99	**1.26**	BLU
2017Q3	-1.08	-1.38	4.08	**1.63**	BLU
2017Q4	-3.43	-2.03	4.51	**-0.95**	BLU
2018Q1	-2.33	-1.22	4.78	**1.23**	BLU
2018Q2	-1.04	-1.46	4.79	**2.28**	BLU
2018Q3	-2.11	-0.77	4.89	**2.01**	BLU
2018Q4	-1.37	-2.08	5.01	**1.56**	BLU

ΔCS – Change in consumer surplus; ΔPS – Change in producer surplus.
FC – upper bound of saving in fixed costs; ΔW - change in total welfare

Table 1-7b: Change of Welfare When Median Quality Products are Removed (Million $)

Year	ΔCS	ΔPS	FC	**ΔW**	Firm
2010Q1	-0.81	-0.70	0.74	**-0.77**	Nokia
2010Q2	-0.68	-0.78	0.88	**-0.58**	Sony Ericsson
2010Q3	-1.09	-1.03	1.26	**-0.85**	Samsung
2010Q4	-0.72	-1.12	1.37	**-0.47**	LG Electronics
2011Q1	-1.19	-1.22	1.39	**-1.02**	HTC
2011Q2	-1.55	-1.25	1.43	**-1.37**	Motorola
2011Q3	-1.18	-1.12	1.67	**-0.62**	Motorola
2011Q4	-2.94	-1.02	1.76	**-2.20**	Samsung
2012Q1	-2.52	-1.70	1.85	**-2.36**	LG Electronics
2012Q2	-2.34	-1.40	2.14	**-1.61**	HTC
2012Q3	-1.44	-1.49	2.18	**-0.75**	LG Electronics
2012Q4	-2.72	-1.33	2.25	**-1.80**	BlackBerry
2013Q1	-1.25	-1.61	2.30	**-0.56**	Samsung
2013Q2	-1.40	-1.79	2.59	**-0.61**	Nokia
2013Q3	-1.82	-1.72	2.72	**-0.82**	Samsung
2013Q4	-3.65	-2.20	2.94	**-2.92**	Samsung
2014Q1	-2.99	-2.01	3.21	**-1.78**	Samsung
2014Q2	-3.23	-2.06	3.54	**-1.75**	Samsung
2014Q3	-4.26	-2.19	4.00	**-2.44**	ZTE
2014Q4	-4.77	-3.17	4.10	**-3.85**	Apple
2015Q1	-3.57	-2.17	4.21	**-1.53**	Motorola
2015Q2	-2.61	-1.94	4.26	**-0.28**	Microsoft
2015Q3	-4.62	-2.26	5.13	**-1.75**	LG Electronics
2015Q4	-2.92	-2.79	5.76	**0.05**	Motorola
2016Q1	-2.74	-2.11	5.91	**1.05**	Kyocera
2016Q2	-2.59	-1.80	6.53	**2.14**	BLU
2016Q3	-1.50	-1.92	6.64	**3.21**	BLU
2016Q4	-5.64	-3.45	6.66	**-2.43**	ZTE
2017Q1	-1.13	-1.91	6.80	**3.76**	Samsung
2017Q2	-1.84	-2.24	7.52	**3.44**	Samsung
2017Q3	-1.61	-2.17	5.91	**2.13**	Alcatel
2017Q4	-5.02	-3.50	9.47	**0.95**	LG Electronics
2018Q1	-2.71	-2.27	8.15	**3.17**	LG Electronics
2018Q2	-1.15	-2.01	8.35	**5.19**	Alcatel
2018Q3	-5.53	-2.37	8.37	**0.47**	Alcatel
2018Q4	-5.32	-3.55	9.08	**0.21**	LG Electronics

ΔCS – Change in consumer surplus; ΔPS – Change in producer surplus.
FC – upper bound of saving in fixed costs; ΔW - change in total welfare

Table 1-7c: Change of Welfare When Highest Quality Products are Removed (Million $)

Year	ΔCS	ΔPS	FC	**ΔW**	Firm
2010Q1	-1.77	-1.26	2.18	**-0.84**	Samsung
2010Q2	-3.28	-2.21	4.26	**-1.23**	Apple
2010Q3	-6.13	-3.54	7.97	**-1.70**	Apple
2010Q4	-3.71	-2.21	5.13	**-0.79**	Samsung
2011Q1	-4.49	-2.87	6.53	**-0.83**	Samsung
2011Q2	-4.98	-2.67	6.80	**-0.86**	Samsung
2011Q3	-3.08	-1.93	4.10	**-0.91**	Samsung
2011Q4	-7.79	-4.42	9.48	**-2.73**	Samsung
2012Q1	-6.48	-3.79	9.08	**-1.19**	Samsung
2012Q2	-6.35	-3.81	8.80	**-1.37**	Samsung
2012Q3	-4.90	-3.22	7.52	**-0.60**	LG Electronics
2012Q4	-9.80	-5.02	10.94	**-3.88**	HTC
2013Q1	-5.83	-3.55	8.15	**-1.23**	HTC
2013Q2	-9.17	-4.78	11.34	**-2.61**	HTC
2013Q3	-6.91	-3.36	9.19	**-1.08**	HTC
2013Q4	-8.90	-4.51	12.35	**-1.06**	HTC
2014Q1	-8.87	-4.19	11.63	**-1.43**	HTC
2014Q2	-7.87	-4.03	9.56	**-2.34**	HTC
2014Q3	-7.52	-4.02	8.86	**-2.68**	Sony
2014Q4	-11.00	-5.37	14.23	**-2.14**	Motorola
2015Q1	-6.81	-3.88	18.82	**8.12**	Motorola
2015Q2	-6.41	-3.88	19.68	**9.39**	Motorola
2015Q3	-9.65	-5.07	18.38	**3.66**	Motorola
2015Q4	-12.11	-6.32	16.02	**-2.41**	LG Electronics
2016Q1	-7.86	-5.00	19.22	**6.36**	Samsung
2016Q2	-5.42	-2.88	14.23	**5.93**	HTC
2016Q3	-7.35	-4.43	12.71	**0.93**	Apple
2016Q4	-17.25	-10.52	21.72	**-6.05**	Apple
2017Q1	-4.92	-3.15	18.38	**10.31**	LG Electronics
2017Q2	-11.13	-6.26	24.91	**7.51**	Samsung
2017Q3	-9.31	-5.50	25.91	**11.10**	Samsung
2017Q4	-15.04	-8.14	27.06	**3.88**	Samsung
2018Q1	-9.20	-4.89	29.17	**15.08**	Samsung
2018Q2	-8.05	-5.86	17.90	**4.00**	HTC
2018Q3	-6.48	-3.10	28.18	**18.61**	Samsung
2018Q4	-15.04	-8.33	29.17	**5.80**	Samsung

ΔCS – Change in consumer surplus; ΔPS – Change in producer surplus.
FC – upper bound of saving in fixed costs; ΔW - change in total welfare

Table 1-8: Change of Welfare When Highest Quality Products are Added (Million $)

	Apple				Samsung				LG			
Year	ΔCS	ΔPS	FC	**ΔW**	ΔCS	ΔPS	FC	**ΔW**	ΔCS	ΔPS	FC	**ΔW**
2011Q1	1.26	0.37	1.41	**0.23**	1.69	0.47	1.94	**0.23**	2.48	0.69	3.10	**0.07**
2011Q2	1.34	0.38	1.15	**0.57**	1.67	0.46	1.58	**0.56**	2.63	0.67	2.52	**0.78**
2011Q3	1.30	0.38	1.03	**0.66**	1.75	0.49	1.41	**0.83**	2.35	0.66	2.26	**0.75**
2011Q4	1.75	0.51	2.41	**-0.15**	2.49	0.69	3.31	**-0.13**	3.65	1.02	5.30	**-0.64**
2012Q1	1.70	0.49	2.22	**-0.04**	2.30	0.60	3.05	**-0.15**	3.12	0.85	4.88	**-0.91**
2012Q2	1.58	0.41	1.90	**0.08**	1.75	0.51	2.61	**-0.36**	2.39	0.69	4.18	**-1.10**
2012Q3	1.33	0.38	1.54	**0.17**	1.95	0.55	2.11	**0.39**	3.11	0.82	3.38	**0.55**
2012Q4	2.42	0.68	3.53	**-0.44**	3.27	0.91	4.85	**-0.67**	4.34	1.20	7.76	**-2.22**
2013Q1	1.55	0.45	1.85	**0.15**	2.18	0.61	2.54	**0.25**	3.08	0.87	4.06	**-0.11**
2013Q2	1.93	0.55	2.32	**0.17**	2.70	0.70	3.19	**0.21**	3.63	1.02	5.10	**-0.45**
2013Q3	1.88	0.54	2.23	**0.19**	2.32	0.65	3.06	**-0.09**	3.37	0.94	4.90	**-0.59**
2013Q4	3.77	0.52	2.67	**1.62**	2.75	0.77	3.68	**-0.15**	3.97	1.09	5.88	**-0.82**
2014Q1	1.76	0.57	2.95	**-0.62**	2.36	0.66	4.06	**-1.04**	3.31	0.92	6.50	**-2.27**
2014Q2	1.97	0.63	2.84	**-0.24**	2.65	0.75	3.90	**-0.50**	3.73	1.03	6.24	**-1.49**
2014Q3	2.15	0.67	3.03	**-0.19**	3.06	0.84	4.16	**-0.26**	4.20	1.14	6.66	**-1.32**
2014Q4	3.22	0.95	5.38	**-1.23**	4.27	1.15	7.40	**-1.98**	6.35	1.70	11.84	**-3.79**
2015Q1	2.20	0.70	3.67	**-0.77**	2.54	0.70	5.05	**-1.81**	3.77	1.03	8.08	**-3.28**
2015Q2	1.90	0.61	3.13	**-0.62**	2.46	0.69	4.30	**-1.15**	3.90	1.07	6.88	**-1.91**
2015Q3	2.40	0.70	3.44	**-0.35**	2.75	0.74	4.73	**-1.24**	4.01	1.12	7.56	**-2.43**
2015Q4	3.41	0.95	4.94	**-0.58**	4.38	1.20	6.79	**-1.21**	6.22	1.69	10.86	**-2.95**
2016Q1	2.04	0.60	2.66	**-0.03**	2.81	0.80	3.66	**-0.05**	3.66	1.02	5.86	**-1.18**
2016Q2	2.33	0.45	1.65	**1.15**	2.51	0.67	2.26	**0.92**	3.45	0.95	3.62	**0.78**
2016Q3	2.35	0.67	2.99	**0.03**	2.84	0.78	4.11	**-0.49**	4.35	1.19	6.58	**-1.03**
2016Q4	3.73	1.04	5.88	**-1.12**	4.96	1.35	8.09	**-1.77**	6.65	1.79	12.94	**-4.50**
2017Q1	2.22	0.65	3.17	**-0.30**	2.85	0.82	4.36	**-0.70**	4.47	1.26	6.98	**-1.24**
2017Q2	2.74	0.79	3.54	**0.00**	3.19	0.90	4.86	**-0.77**	4.25	1.17	7.78	**-2.35**
2017Q3	2.27	0.66	2.83	**0.11**	3.18	0.89	3.89	**0.19**	4.17	1.16	6.22	**-0.88**
2017Q4	3.54	1.03	5.90	**-1.34**	5.39	1.53	8.11	**-1.19**	6.56	1.83	12.98	**-4.59**
2018Q1	1.53	0.44	1.75	**0.23**	2.47	0.68	2.40	**0.75**	3.72	1.03	3.84	**0.91**
2018Q2	1.97	0.60	2.89	**-0.32**	2.92	0.85	3.98	**-0.20**	3.88	1.13	6.36	**-1.35**
2018Q3	1.86	0.55	2.54	**-0.12**	2.55	0.71	3.49	**-0.23**	3.25	0.91	5.58	**-1.42**
2018Q4	2.79	0.78	4.46	**-0.89**	3.16	0.90	6.14	**-2.07**	5.23	1.45	9.82	**-3.15**

ΔCS – Change in consumer surplus; ΔPS – Change in producer surplus.

FC – upper bound of saving in fixed costs; ΔW - change in total welfare

List of Figures for Essay One

Figure 1-1: Avarage Number of Smartphones Offer by Firms

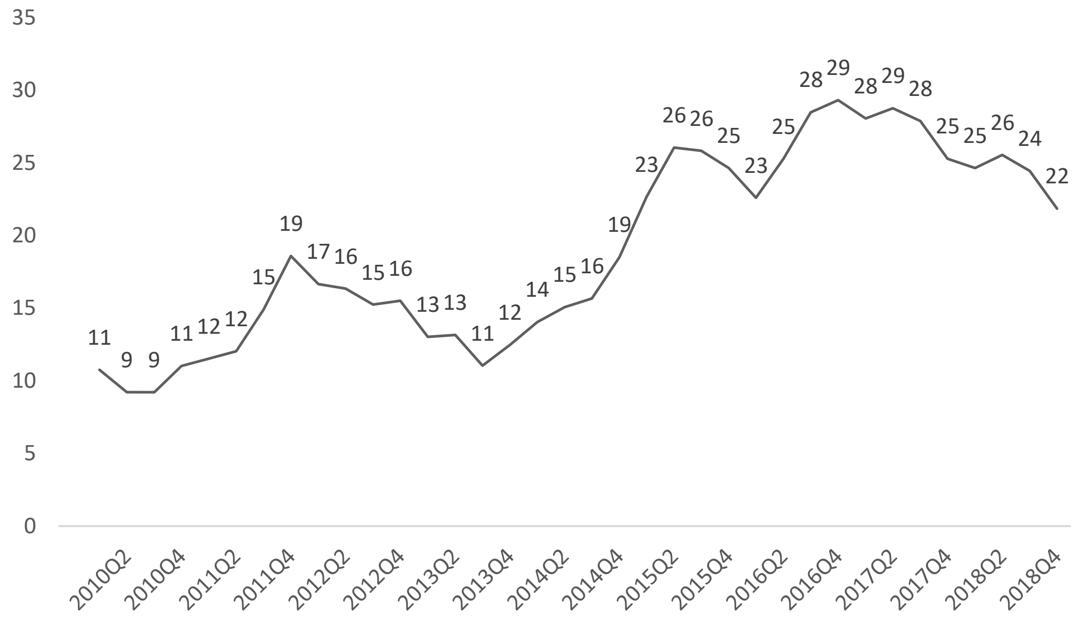


Figure 1-2: Smartphone Quality Over Time

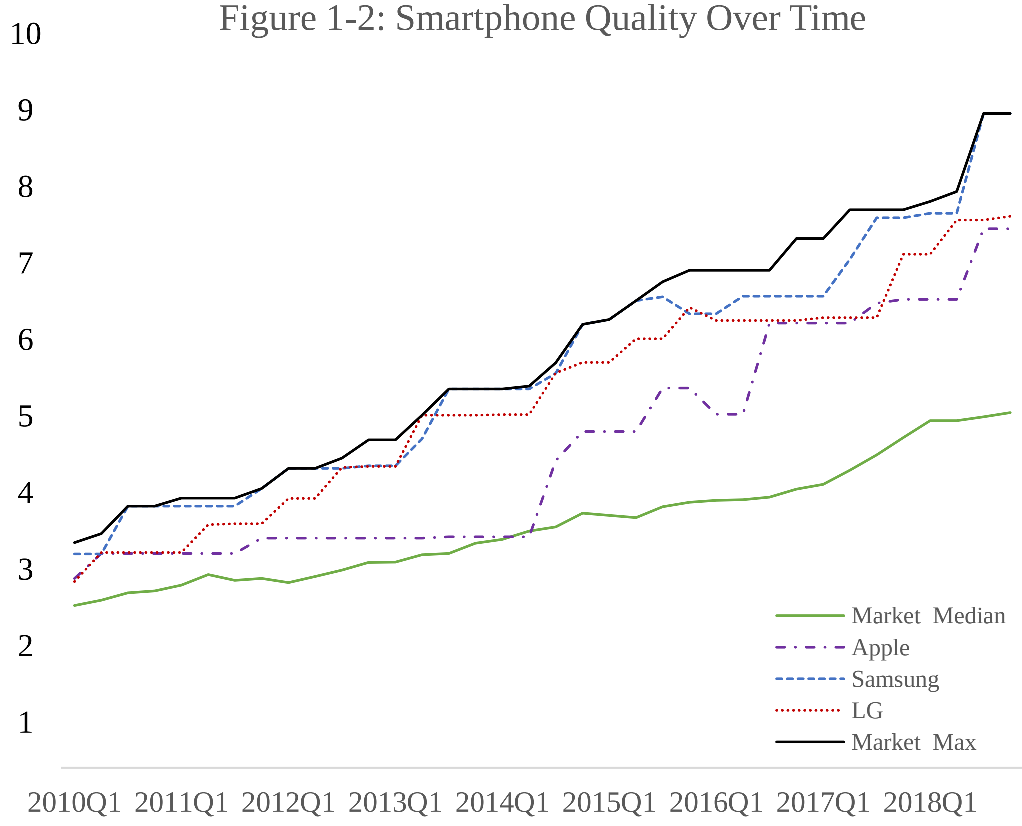


Figure 1-3: Number of Products

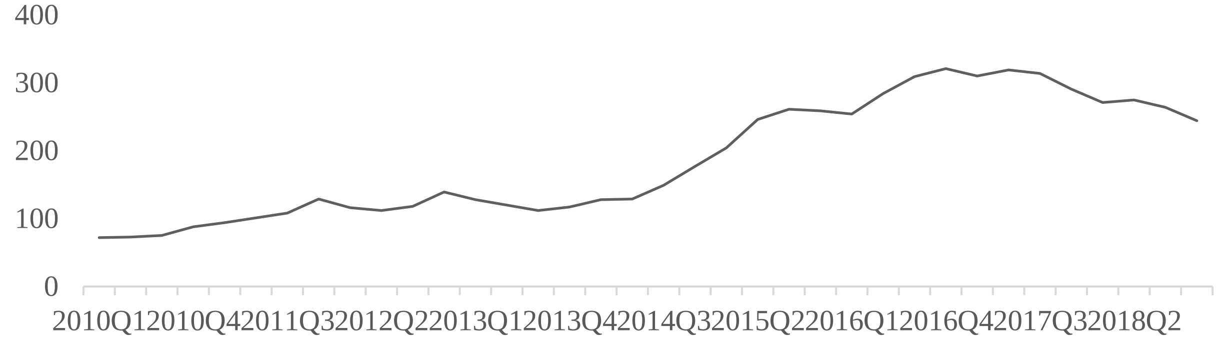


Figure 1-4: Variety Measure

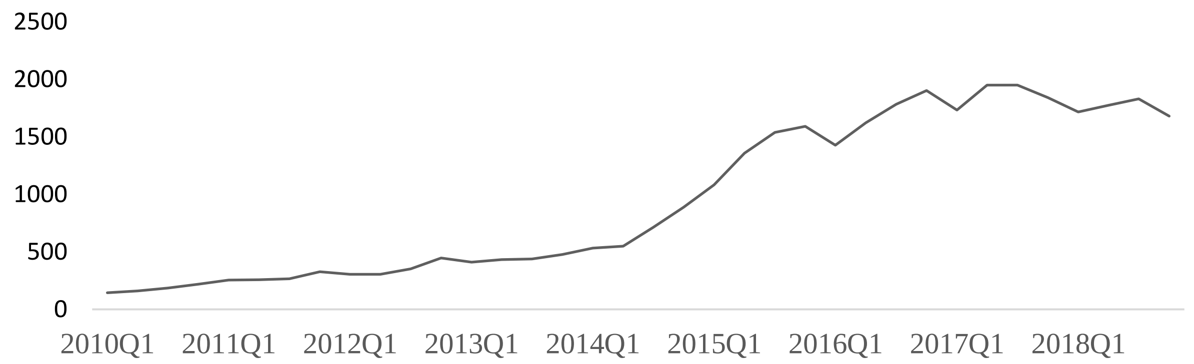


Figure 1-5a: Upper Bound of the Fixed Cost

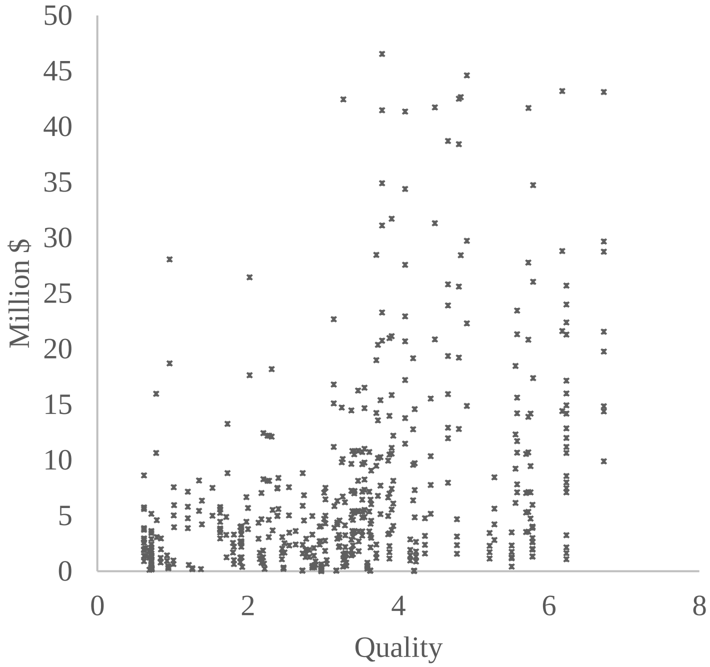


Figure 1-5b: Upper Bound of the Fixed Cost

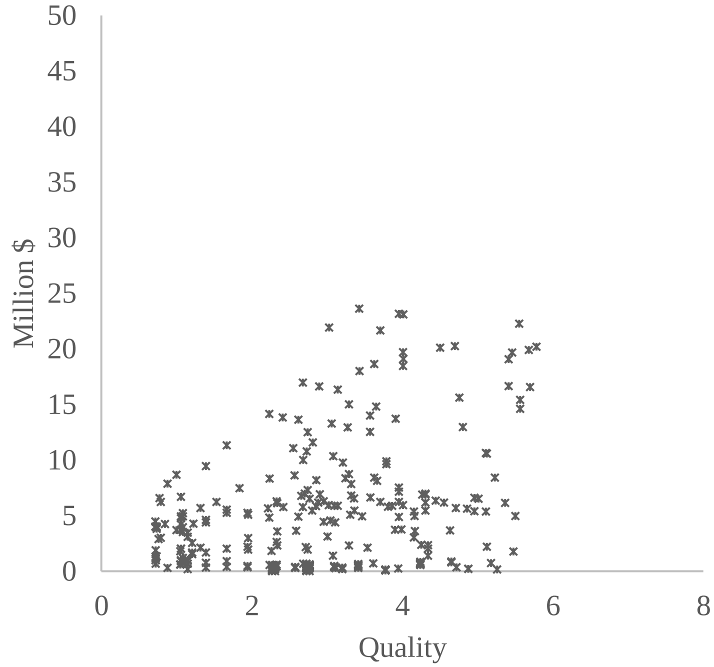


Figure 1-6: Percentage Change in Consumer Surplus When a Product is Removed

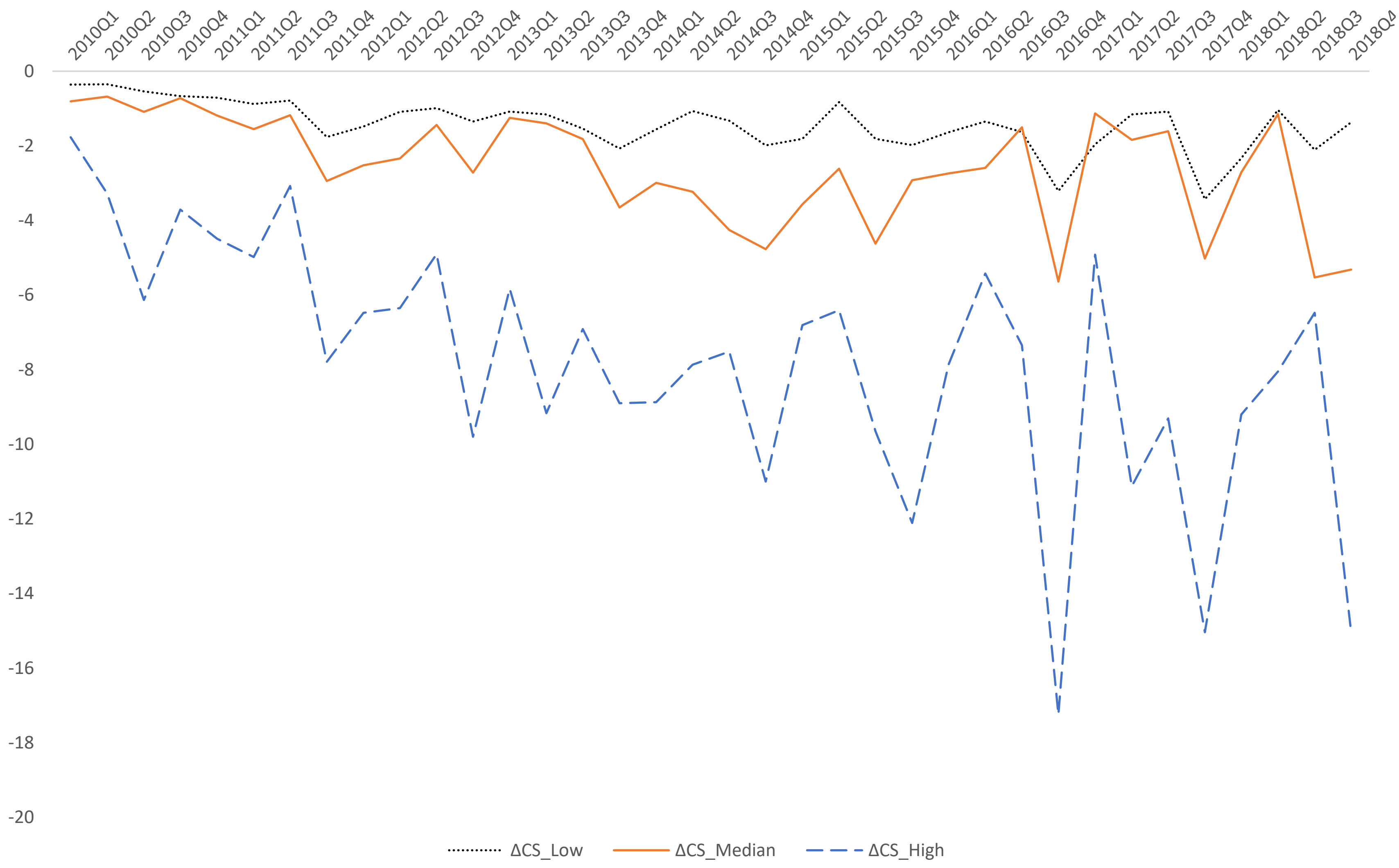


Figure 1-7: Quality of Products in Last Quarter of 2018

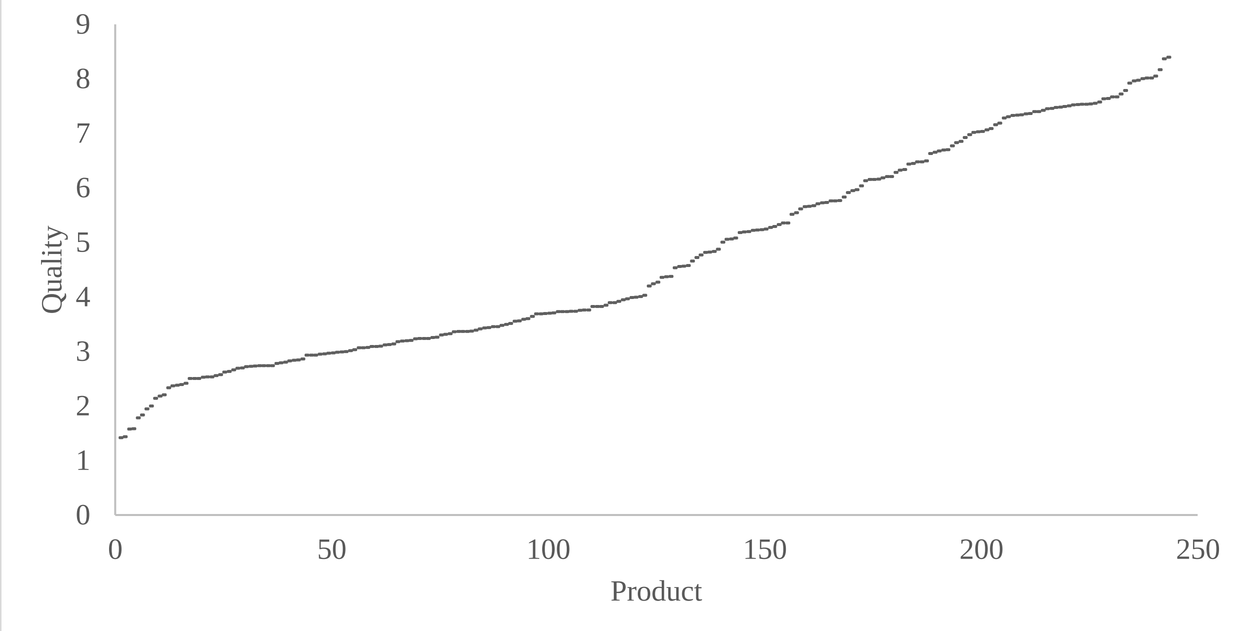
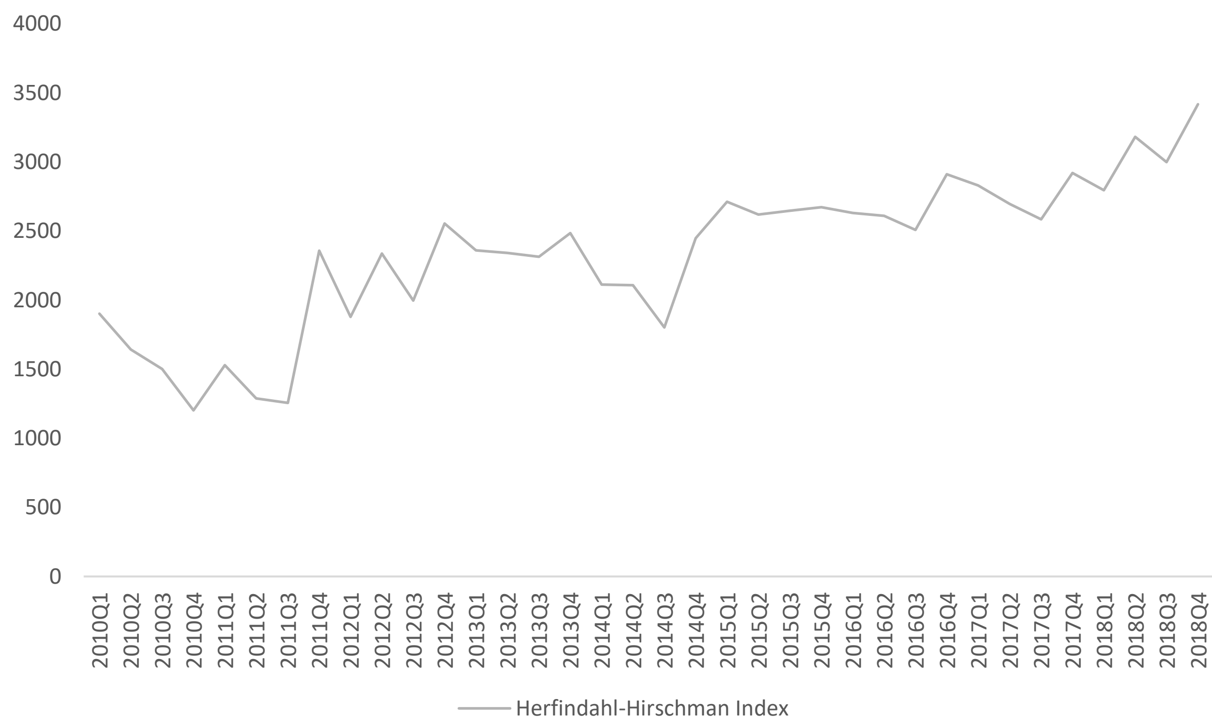


Figure 1-8: Herfindahl-Hirschman Index



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