

EMPIRICAL ANALYSIS OF ONLINE SALES DATA WITH IMPLICATIONS TO
PRICING

by

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ABSTRACT

EMPIRICAL ANALYSIS OF ONLINE SALES DATA WITH IMPLICATIONS TO PRICING

Sales dynamics are investigated on a multi-seller online platform through analyzing the relationship between price and quantity. 376 days long sales transaction data of smart phones by Apple, Samsung and Huawei are observed. Since there is simultaneous causality between price and quantity, instrumental variables (IV) are identified and used in regression models to fix the bias in results. Two-stage Least Squares Regression (2SLS) models are formed including price as endogenous variable and quantity. Instrumental variables which are correlated with endogenous variable (price) and independent of the error term are put in these models with controls. A parametric analysis is conducted through several products with daily data. Price and ratio of stock-out sellers of the product are found significantly effective on sales quantity. Moreover, simultaneous bias which is fixed by 2SLS regression models is shown over several models through comparison with Ordinary Least Squares (OLS) regression results. Additionally, since the data observed includes zero sales price data, the selection bias (which would exist if this information is excluded) is fixed and shown. Besides describing the dynamics, these models are also used for predicting sales quantity. On the other hand, consumer choice models are formed as Multinomial Logit to describe consumer choice behaviour on the online platform during the time observed. Model results confirm that customers are more determined in their product selection and first decide on the product then compare among its sellers. Some features like brand reputation, seller service are found to be significantly effective on consumer choices.

ÖZET

ÇEVİRİMİÇİ SATIŞ VERİLERİNİN DENEYSEL ANALİZİ VE FİYATLANDIRMAYA ETKİLERİ

Çevrimiçi satış dinamikleri fiyat ve satış miktarı arasındaki ilişki gözetilerek incelenmiştir. Bir çevrimiçi alışveriş platformu üzerinde Apple, Samsung ve Huawei marka akıllı telefonların 376 günlük satış verisi analiz edilmiştir. Fiyat ve satış miktarının birbirlerini karşılıklı etkileme durumundan dolayı elde edilecek sonuçlarda sapma beklenmektedir. Bu nedenle, araç değişkenler kullanılarak İki Aşamalı En Küçük Kareler yöntemi ile regresyon modellemesi yapılmıştır. Modellerde bağımsız değişken olarak ürün fiyatı, bağımlı değişken olarak ise satış miktarı, bazı kontrol ve araç değişkenleri ile birlikte kullanılmıştır. Araç değişkenlerinin fiyat ile ilişkili ancak satış miktarından bağımsız olması gözetilmiştir. Birkaç ürün belirlenmiş ve günlük veriler ile parametrik analiz yapılmıştır. Ürün fiyatının ve stoksuz kalan satıcıların oranının satış miktarı üzerinde etkili olduğu istatistiksel olarak gösterilmiştir. Aynı zamanda, karşılıklı ilişki kaynaklı oluşacak sapma da Sıradan En Küçük Kareler Yöntemi ile oluşturulan model sonuçları üzerinden saptanmıştır. Ek olarak, sıfır satış bilgilerine sahip olduğu için bu bilgi harici yapılan analiz ile aradaki farklar belirlenerek bu anlamda da oluşacak sapma gösterilmiştir. Satış dinamiğini açıklamanın dışında bu modeller satış miktarı tahmini için de kullanılmıştır. Bunların yanı sıra, Multinomail Logit model ile müşterilerin çevrimiçi alışveriş platformu üzerindeki satın alma davranışları açıklanmıştır. Tüketicilerin ürün seçiminde daha kararlı oldukları ve önce bu kararı vererek daha sonra o ürünün satıcıları arasında seçim yaptıkları sonucuna varılmıştır. Bununla paralel olarak, marka değeri ve/veya satıcı servisi gibi bazı özelliklerin satın alma davranışına etkileri görülmüştür.

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1. INTRODUCTION

Online transformation affects not only industries but also people's daily lives. Banks are now integrated with digital tools, in factories there are robots making the production, packaging etc. and FMCG (Fast Moving Consumer Goods) companies tend to control their supply chain process mostly online. One can give such limitless examples from industry. Meanwhile, people are now more likely to make financial transactions, communicate and even are taught or work through computers or mobile devices. Covid-19 pandemic accelerates this transformation both in industries and people's daily life.

In parallel, certain aspects of sales have been changing as well. Today, there are numerous e-commerce companies and people are more likely to search a product/category/brand online, list relevant results and click on the product's page, read comments, look at price and make the purchase again online. They were used to go to a physical store, walk around there, touch the product, look at its package and label then give money or card to the salesperson. Different sales strategies have been forced to be applied. For instance, a need of changing product's shelf turns to increase its rank in placement in the search page.

Moreover, a major difference is related with the price information. A person could go to several stores and investigate the price of a specific product but one can see that this can be so limited. On the other hand, now it is easy to see varying prices of the same product in minutes or even seconds. The question of how price affects the sales becomes more vital than ever. In sales dynamics, price and quantity relationship plays a major role. Seller has to ask how their sales quantity will be affected by changing their prices. Price is still a key factor on consumers' purchasing behaviour and competition in the market.

To understand the online market dynamics and make conclusions for sellers to

compete successfully in such markets, the relationship between price and quantity is investigated. To do so, sales transactions on an online platform is observed.

The platform studied in this thesis is a pure marketplace where sellers have full control on their prices. Since the platform is not a seller it is like Ebay or n11 whereas different from Trendyol or Amazon. The platform may offer discounts to the sellers. There is competition in the market by many sellers and the prices are equilibrium prices.

A sales data from the online platform of 376 days, from 07/09/2018 to 18/09/2019 is observed. It includes 62 different features about 24 smart phone models of brands Samsung, Apple and Huawei with their daily sales transactions. A parametric analysis is made on three models, such as Apple iPhone 8 64 GB, Huawei P20 Lite 64 GB and Apple iPhone 8 Plus 64 GB. These are taken as representatives of the competition in the market. Regression models are formed both from a seller's (the top seller who sold this product at most) point of view and market overview.

Relationship between price and quantity has simultaneous causality which creates a bias in model results. To avoid this, instrumental variables (IV) are used and 2SLS (Two Stage Least Squared Regression) models are formed. Selection of IVs is critical and tests are applied on candidate variables to check their correlation with endogenous variable (price) and independence of outcome's (quantity) error term. Variables are obtained differently for each model and they are average price information from a different category on the same platform, the exchange rate of United States Dollar (USD) to Turkish Lira (TL) - since products' original prices are in USD -, the number of sellers of the same product and the proportion of sellers given discount by the platform.

These models constructed show the significance of price on quantity as well as the simultaneous bias with comparison with the model results not including IV approach. Likely, the sales data observed includes information of zero sales and so the selection

bias is also fixed and is proven by comparing with the model results over only sales data. After discussing the descriptive power of 2SLS regression models - both over a single seller and through the market, with fixing two biases described - predictions are made over them. It is evaluated how these models can be used for the platform and/or sellers there.

On the other hand, consumer choice models are formed as Multinomial Logit (MNL) to understand the buying mechanism/behaviour of customers of the platform. Representative two products (Apple iPhone 8 64 GB and Samsung Galaxy S8 64 GB) and their top three sellers (who have high sales volumes) are selected. 46 days that all six alternatives are available to a customer are investigated. Thus, market competition is thought to be well described during this period. Also, two step decision mechanism for purchase is modelled with creating nests of products and sellers. Customers on the platform are observed as they first decide on the product then make selection among its sellers. The purpose of MNL consumer choice models is to explain the observed sales in the marketplace.

Moreover, some scenario analysis is made with changing prices of product alternatives to see the dynamics of consumer behaviour with different prices. People are seemed to be more determined in their product decisions and also affected by some alternative specific conditions. These can be brand reputation, seller's rating and/or service quality.

The rest of the thesis is organized as follows: Chapter 2 provides a literature review and positions this thesis in the literature. Chapter 3 summarizes the data observed and shares which information is included and the driven parameters that are used in the analysis. Chapter 4 analyzes the sales dynamics of sellers on the platform through 2SLS regression models. Chapter 5 includes the MNL consumer choice models and results obtained. Lastly, Chapter 6 concludes the thesis and summarizes the work done.

2. LITERATURE REVIEW

Previous work which have described the price-demand relationship, online platform operations, IV approach and 2SLS regression models and MNL models are observed.

Firstly, price-demand relationship is analyzed through several price and demand models formed.

Chen and his friends introduce a joint decision making idea considering both pricing and inventory replenishment. They argue to divide a replenishment period according to some levels and adjust different prices in each period. The paper refers to the well known (s,S) policy. At the end, a joint model with two prices is recommended. While constructing models, this joint decision making point of view is taken under consideration [1].

Huang et al. mention numerous different demand models which depend on price, rebate, lead time, space, quality and advertising. In each category, single firm-demand models are analyzed as well as game theoretic multi firm models involving strategic interaction. They state main properties, advantages and disadvantages of those models. Models of price, quantity and consumer utility are updated versions of these main samples. It is a reference for constructing price-demand models in this thesis [2].

Sayarshad and Gao introduce a new framework for the design of a dynamic non-myopic inventory and delivery network between suppliers and retailers under the assumption of elastic demand. They propose a dynamic approach which simultaneously incorporates inventory, routing, and pricing that aims to maximize social welfare of customers (customer waiting times, inventory holding, lost-sales costs, and delivery costs are considered). The way of thinking goes parallel with the Multinomial Logit models constructed to observe customer utility gained from choices made [3].

Parker and Olsen create a model that the firms have direct demand not depending on each other but some proportion of the sales lost will shift to a competitor. The article defines up-to and basestock policies for firms and shows an Equilibrium in Stationary States (ESS) exists where same strategy is played in each period. It also proves that ESS is a Markov Equilibrium under some conditions. This is helpful to understand a competitive environment and possible interactions between its players just like an online retail market and its sellers [4].

Adida and Perakis state a joint dynamic pricing and inventory control problem. Their goal is to address demand uncertainty using various robust and stochastic optimization approaches. For each of these approaches, both a closed loop and an open loop formulations are introduced and compared with each other. They conclude that the affine adjustable robust approach performs well (when compared to the other approaches such as dynamic programming, stochastic programming and robust open loop approaches). Appearance of dynamic pricing and joint thinking with inventory is common so the models formed here help [5].

Kim points out the importance of competitors' information for firms where he states this valuable knowledge is often not available for them. As the result of the research, it is concluded that when they receive this information, companies are 17 percent more likely to change their prices. This is a reference for supporting the models including competitor prices [6].

Bijmolt et al. have a publication arguing price sensitivity becomes more vital than ever it is and outcomes obtained by historical studies may change. This change can be caused by differentiation in market characteristics as well as research methodology. They show different findings compared with old studies. For instance, they argue heterogeneity is not significantly effective on elasticities unlike what is said in literature in the past [7].

Secondly, there are papers with results about platform operations by analyzing real life examples.

Zhang et al. set up a randomized experiment on the online booking platform Alibaba such as giving promotions to the control group to see its effects. They look at both short and long term impacts on customers and also the spillover effects. It is seen that product views, purchase indices and expenditures raise when customers have this promotion. On the other hand, a direct strategic and cross mechanism effects are observed on customers. So when there is a discount, customers' reference prices (ie. amount that they are willing to pay) decrease and a tendency to look for other promotions appears. Moreover, this attitude is also valid toward other retailers (the ones who did not offer promotion) which proves the spillover effect. It helps to understand customer behavior while building customer utility models [8].

Gibbs et al. examine hosting behaviors on Airbnb which they define as unique and complex platform. They provide a comprehensive look at the Airbnb pricing across five different markets, over a 12-month period and compared to hotel pricing strategies. Key questions it seeks to answer are to what extent Airbnb hosts manage dynamic pricing, how their pricing fluctuations compare with hotels and whether higher price variation can be related to certain host and listing characteristics. The point of view from a seller in an online retail platform is similar and common questions are asked [9].

Thirdly, some publications about the IV approach and 2SLS regression models are included.

Li et al. examine the effect of competition on pricing strategy through hotels in New York City. It questions which competitors to look at and how for pricing. While coming out with a price model depends on competitors' prices, two challenges are faced such as simultaneity bias and high dimensionality. Authors introduced a new instrumental approach to overcome these. As a result, it is found out that actually only a portion of competitors (e.g. similar type of hotels or the ones nearby) are considered

while adjusting prices. This thesis also includes price models including instrumental variables and has similar questions regarding sellers [10].

Cachon et al. investigate inventory and sales through facing the challenge of endogeneity in this relationship. They got benefit from instrumental variables and explain how a variable can be selected as a strong instrument. They came up with a result of increasing inventory may lower sales whereas an allocation strategy that maximizing variety but minimizing duplication (i.e. remaining the total number constant) can be beneficial. For constructing two stage least squared (2SLS) regression models including selecting instruments and testing their strength, this paper is a reference [11].

Hanck et al. wrote a book called "Introduction to Econometrics with R". It is a guide to construct 2SLS regression models and use IV approach. They explain the theory as well as show applications on software program R [12].

Lastly, related Multinomial Logit (MNL) literature is also reviewed.

Fisher et al. develop a consumer choice model. They introduce an empirical model looking at consumer choices among sustainable products from multiple retailers. Since demand shocks that are not observable to researches create endogeneity of data, randomized prices are used to determine price elasticities. Also, due to the lack of competitors' sales information, stock outs are used as a source of variation to the consumer choice set. At the end, the developed model which increases revenue is chosen as the best-response pricing strategy. The Multinomial Logit models, estimating consumer's utility of choosing a product from a seller, are formed through a similar thinking and methodology [13].

Train explains several models through chapters in his book "Discrete Choice Methods with Simulation". In Chapter 5, models and theoretical information regarding choice probabilities is the guide to construct Multinomial Logit models [14].

3. DATA

To get specific answers for the research questions described as well as investigate the relationship between price and the quantity, sales transaction data of smartphones from an online platform is analyzed. It is really significant for the analysis that this data also includes transactions that are not resulted with a sale. Thus, there exists information about prices offered for the products that could not be sold.

The data observed includes 62 different features about 24 smart phone models of brands Samsung, Apple and Huawei related with their daily sales transactions between 07/09/2018 and 18/09/2019 (one year period) on an online retail platform. The platform is a pure marketplace where many sellers sell their products. Platform owner is not a reseller. Some main features are listed in Table 3.1 with their description and a single sales transaction example.

Table 3.1. Information Included in Observed Data.

Date	2018-09-07
Brand	Apple
Product ID Number	238192972
Seller ID Number	2070783
Title	Apple iPhone 8 Plus 64GB (Apple Türkiye Garantili)
Price	6500
Discounted Price	5309.9
Platform Discount Value	210.1
Seller Discount Value	980
Sale Status	On Sale
Product Create Date	2018-02-19 17:15:25.536
USD/TL Exchange Rate	6.6
Price (in USD)	1045.5

Table 3.1. Information Included in Observed Data (cont.).

GTIN (Barcode No)	190198454225
Model	Apple iPhone 8 Plus 64 GB (Distribütör Garantili)
Quantity	13
Revenue	69028.7
Double 11 Campaign	FALSE
Platform Discount	TRUE

3.1. Brands and Models

Sales transactions of three major brands in smart phone industry form the observed data with their most recent and trendy products. Apple's iPhone 8 and X models as well as "Plus" editions, Huawei's P20 Lite and Pro products and Samsung's S8 and S9 smart phones as well as again their "Plus" editions are product choices. Moreover, storage capacity (64, 128, 256 GB) and guarantee options (by distributor or importer) varies for most of these smart phones. Also, Samsung offers "duos" options which are phones with double SIM cards. In total, there are 8,4 and 12 product models offered by Apple, Huawei and Samsung, respectively. The whole list is in Table 3.2.

Table 3.2. Product Models.

Brand	Model
Apple	Apple iPhone 8 256 GB (Distribütör Garantili)
Apple	Apple iPhone X 64 GB (Distribütör Garantili)
Apple	Apple iPhone 8 Plus 64 GB (Distribütör Garantili)
Apple	Apple iPhone 8 64 GB (Distribütör Garantili)
Apple	Apple iPhone 8 Plus 256 GB
Apple	Apple iPhone X 256 GB
Apple	Apple iPhone 8 64 GB (İthalatçı Garantili)

Table 3.2. Product Models (cont.).

Apple	Apple iPhone X 64 GB (İthalatçı Garantili)
Huawei	Huawei P20 Lite 64 GB (Distribütör Garantili)
Huawei	Huawei P20 128 GB Duos
Huawei	Huawei P20 Lite (İthalatçı Garantili)
Huawei	Huawei P20 Pro 128 GB (Distribütör Garantili)
Huawei	Huawei P20 128 GB
Samsung	Samsung Galaxy S8 64 GB(Distribütör Garantili)
Samsung	Samsung Galaxy S8 Plus
Samsung	Samsung Galaxy S9 Plus (Distribütör Garantili)
Samsung	Samsung Galaxy S9 (Distribütör Garantili)
Samsung	Samsung Galaxy S8 64 GB (İthalatçı Garantili)
Samsung	Samsung Galaxy S8 Plus Duos 64 GB
Samsung	Samsung Galaxy S9 Plus 128 GB
Samsung	Samsung Galaxy S9 Plus 256 GB
Samsung	Samsung Galaxy S9 64 GB Duos
Samsung	Samsung Galaxy S9 Plus 64 GB
Samsung	Samsung Galaxy S9 Plus 64 GB Duos

3.2. Sellers

There are numerous sellers of each single product listed above. Apple is the topmost brand since its products are sold by 137 different sellers, then Samsung and Huawei follow with 83 and 71 sellers on the online retail platform. Moreover, daily number of sellers changes over the time period observed for all of them. For each brand, number of sellers reach a peak point just after the beginning of time period analyzed and then a general decreasing trend is observed besides small fluctuates between several days. However, Samsung is observed being more stable in terms of seller numbers through the end of the time period unlike its two competitors. The graph in Figure 3.1 demonstrates stated observations.

Note that the main reason for the decline in seller numbers is a "cleaning" process that the platform initiated in October 2018 where they deleted inactive sellers, merged multiple accounts of the same seller etc.

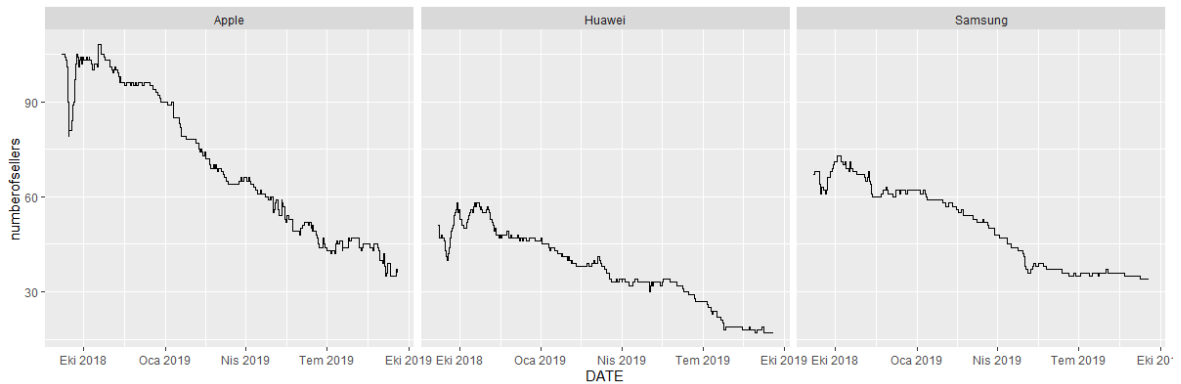


Figure 3.1. Daily Number of Sellers over 376 Days.

3.3. Price

Initially, please remember that the price information includes the unsuccessful transactions so it is observable that a seller cannot sell a product with what price. This information is usually not observable for researchers and a strong advantage to have sharp price sensitivities through the analysis.

Price offered for products varies significantly according to brand. However, there is significantly less differentiation between prices offered by sellers of the same product. Moreover, no notably large change in prices is observed over time. Thus, brand factor, i.e. the reputation, is a dominant factor on price. Table 3.3 gives price information over 376 days according to brand including minimum, maximum, mean, median values as well as quartiles. Note that discounted prices are reported since these are the amounts paid by customers for products.

Table 3.3. Price Variation over 376 Days.

Average Daily Price (TL)	Apple	Huawei	Samsung
Minimum	6099	2794	4139
First Quartile	6230	3185	4246
Median	6297	3294	4329
Mean	6323	3354	4362
Third Quartile	6339	3580	4435
Maximum	7115	3852	4794

Apple products are the most expensive among its competitors offered with an average price of 6323 TL and varies from approximately 6000 to 7000 TL. Then, Samsung follows with an average price of 4362 TL and changes with fractions over 4000 TL. Lastly, Huawei offers cheapest products compared to those two and its mean price is 3354 with fluctuates between 2794 and 3852. Sellers change prices in an interval of nearly 1000 TL for all products over time whereas mean prices are significantly different based on the brand.

3.4. Sales

In 376 days, 33,303 smart phones of above mentioned models are sold on the online retail platform. Over half of these products sold are Huawei's (17,041) despite the less number of sellers than its competitors. Apple sold 10,040 and Samsung has 6222 phones over this time. Thus, again a brand affect is strongly visible. Most probably, this huge dominance of Huawei in terms of sales is caused by its low prices.

On the other hand, much more significant factor on sales (independent of seller or product) is the double 11 campaign. On 11th of November, there is a discount on most of the products and it multiplies daily sales of nearly all products in every category on the online retail platform. Just on that day, Apple sold 1437 smart phones, 3442 Huawei and 1074 Samsung products are sold which is over 14 percent, 20 percent

and 17 percent of their total sales over 376 days, respectively. Thus, Figure 3.2 shows how daily total sales of each brand changes over time. Note that November, 11 is not included in Figure 1.2 to be able to observe sales trend without dominance of the campaign.

Moreover, it is seen in Figure 3.2 that even though this graph does not include the date of double 11 campaign, there are still some peak points in terms of sales most probably due to such other discounts and/or campaigns. One can see these increases exist mostly for Huawei and Samsung products whereas Apple smartphones do not draw such high peaks. Like this difference between brands, again Samsung and Huawei phones show a dying off through the end of the time horizon observed unlike Apple.

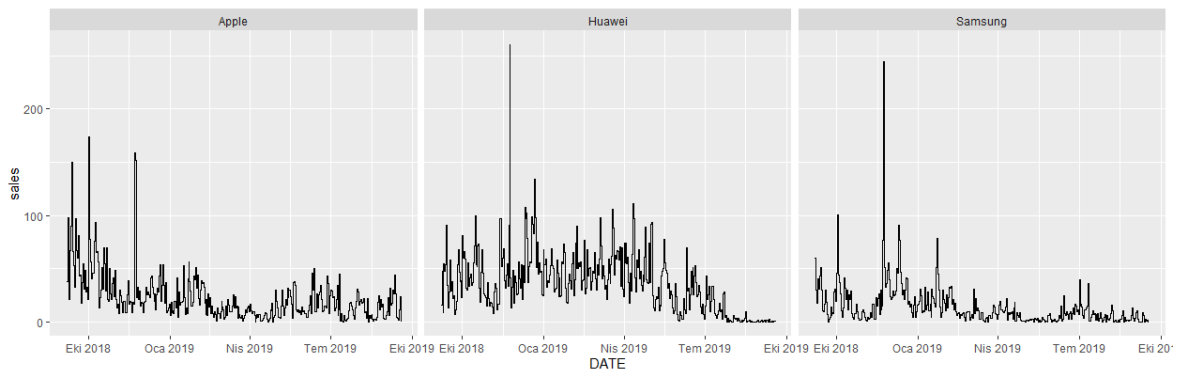


Figure 3.2. Daily Total Sales over 375 Days (November 11 excluded).

Here, another significant observation is actually there is no notable amount of discount occurs on November, 11 so it is slightly strange to see such increase in daily sales. Prices offered on that day for products of these three brands are compared prices over the rest of days observed to show this result. The comparison is given in Table 3.4. While there is very slight decrease in daily average prices offered for Apple products, Samsung and Huawei made sales even with higher price on average on that day. Moreover, minimum prices offered for products belonging to all of the three brands are lower for the time period excluding double 11 campaign rather than the campaign date.

Table 3.4. Price Comparison for Double 11 Campaign.

Brand	Prices on 11/11/2018		Prices over 375 Days	
	Average	Minimum	Average	Minimum
Apple	6320	3899	6358	988*
Huawei	3643	1999	3429	1729
Samsung	4445	2969	4399	1559

Note: Prices are in Turkish Liras

*Price is offered by a single seller for 3 products during 4 days and the total sales quantity is zero, the minimum price offered excluding these transactions is 1869 Turkish Liras

Additionally, to support observations over sales, revenues of each brand over the time period analyzed can be shown, as well. Apple is again the winner in terms of total revenue over 376 days with over 57 million TL, followed by Huawei which has over 47 million TL total revenue and Samsung with 23.7 million TL. The comparison graph of revenues is given in Figure 3.3. November, 11 is included here to figure out its huge effect. One can observe that Huawei has the highest revenue over double 11 campaign despite of having less revenue in total than Apple.

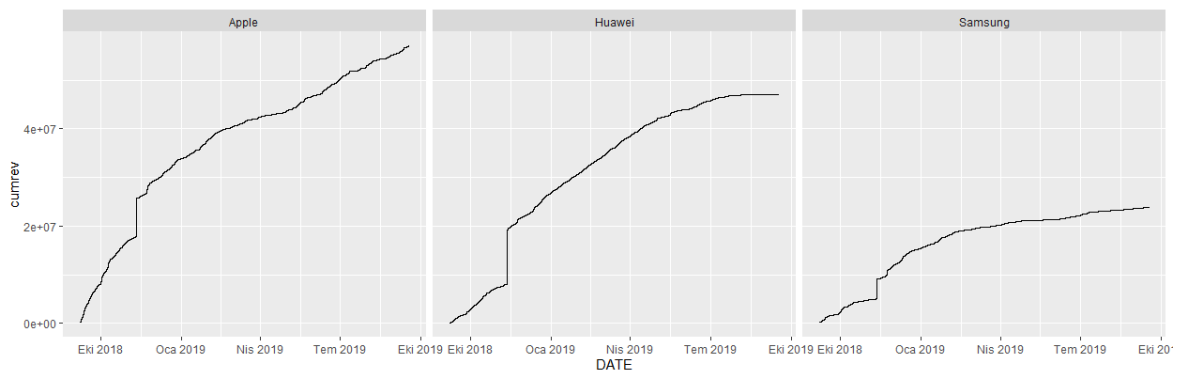


Figure 3.3. Cumulative Revenues over 376 Days (in TL).

Another observation is made to see whether there is a time series effect on the sales data. Since the data includes daily sales transactions, daily total sales quantities are taken as time series and autocorrelation is checked. Table 3.4 shows the autocorrelation level among the daily total sales of smartphones on the platform with respect to changing lag measures. Here, lag 0 means the data is compared with itself so a perfect correlation is expected. Lag 1 means each data is compared with the previous one, i.e. the total sales of a single day is compared with the previous day's data. One can see the low autocorrelation found through this analysis. Hence, analysis is made over the data without considering it as time series.

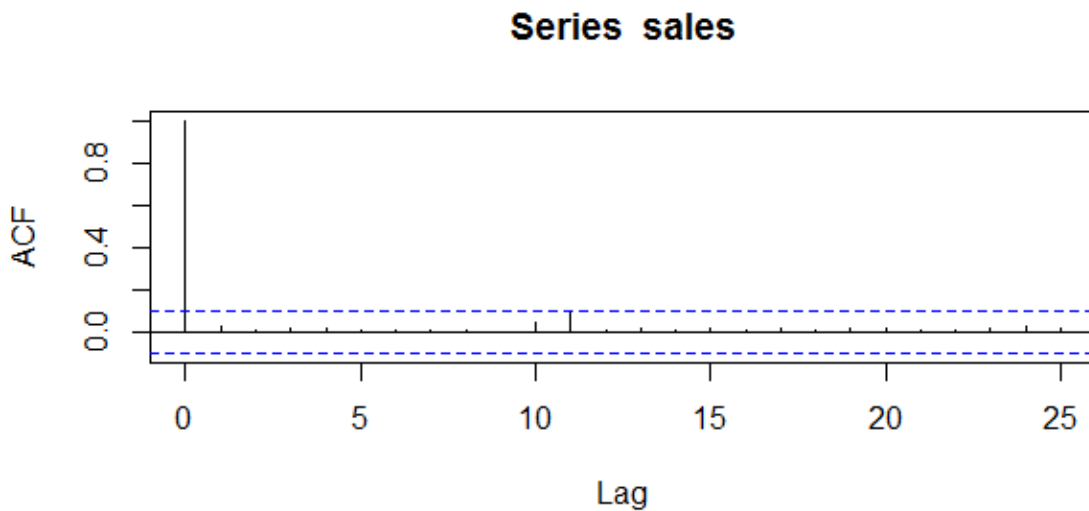


Figure 3.4. Autocorrelation of Sales Data over Time.

3.5. Discounts

The platform may give discounts to some sellers on a daily basis so they reduce their prices besides seller's own discount. This is of course significantly beneficial for sellers and may affect their sales. Decision on sellers to receive this discount and the reduction amount is made just for a single day. Table 3.5 shows in total, how many times this discount is given to how many sellers according to brand.

Table 3.5. Total Number of Platform Discounts over 376 Days.

Brand	Platform Discount Occurrence	Sellers
Apple	2731	30
Huawei	1994	19
Samsung	2098	15

Moreover, proportion of sellers who are given discount by the platform is an essential information which can affect the sales dynamics, i.e., may have an impact on the quantity. Figure 3.5 shows how this ratio changes over time on a daily basis.

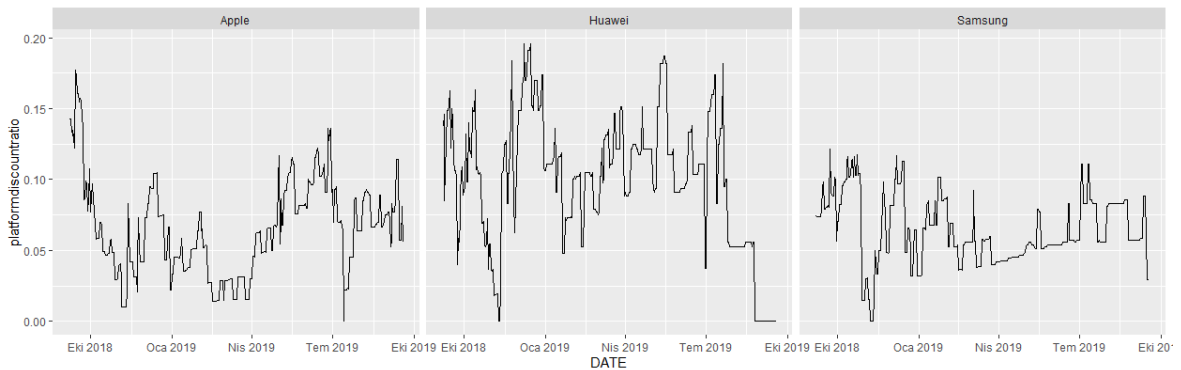


Figure 3.5. Sellers with Platform Discount Ratio over 376 Days.

3.6. Stocks

Availability of a product is essential for its sales. Existence of different alternatives can affect sales of each seller and it is related with sellers' stock levels for products. When a seller is left without any stock on a day, it may change the sales dynamics. It will be beneficial to observe daily ratio of sellers who are left without any stock so it helps to figure out frequencies of stock-outs and replenishment periods. Ratio of stock-out sellers on the platform over 376 days are shown in Figure 3.6.

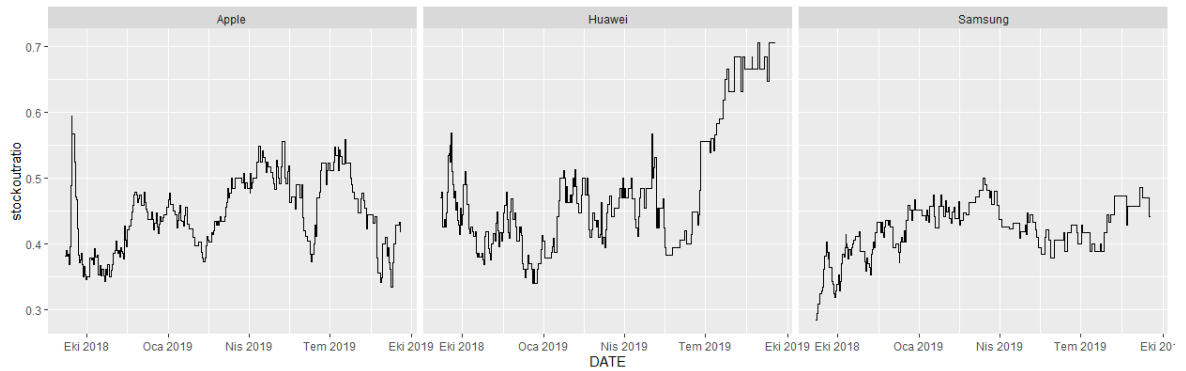


Figure 3.6. Stock-out Sellers Ratio over 376 Days.

It is observed that when sellers of Apple products are left without any stock, they wait more to supply products when compared with their components. On the other hand, replenishment period is thought to be shorter for Huawei and Samsung since the rise and falls in the ratio are generally followed by each other with shorter ranges. Also, there exist a quiet long period with significantly high stock-out sellers proportion for Huawei through the end of the time horizon observed. This can be caused by strongly decreased number of Huawei sellers (more than the other two brands, as shown in Figure 3.1) for this period which logically increases this ratio. This may be the dying off effect for Huawei products.

4. DEMAND - PRICE DYNAMICS OF SELLERS

One of the main objectives of this research is understanding the seller behavior in pricing a product and selling it on an online platform. To be able to understand such behavior, most importantly the relationship between price of a product and the quantity sold for that price should be observed. In other words, one needs to get an answer to how effective the price is on the sales amount as well as which other features can be significant in the same manner. It is aimed to make that inference to this causal question through observation data. Mainly, relationship between a product's price and its sales quantity is to be investigated. However, there may be simultaneous causality in this relationship and unexpected results may be observed when the independent variable (outcome) is correlated with the regression error term because of simultaneity [12].

In other words, price and quantity may affect each other at the same time and it will create estimation bias in the model. To avoid the simultaneity bias in this relationship, an instrumental variable (IV) approach is needed. An IV will be used to estimate the price first, then that estimated value will be used as the price into the model while reaching the quantity value. Thus, a two-stage least squares regression model (2SLS) should be formed accordingly [12]. Here, selection of an IV is so important. A good IV should be directly correlated with the price but not with the quantity. Moreover, some control variables can be included in such a model to ensure the comprehensiveness, so the relationship is significantly represented in the model.

Such models are formed through analysis of several products from a seller's perspective as well as overview of the market. When sales amount of each product sold on the platform is considered, Huawei P20 Lite 64 GB and Apple iPhone 8 Plus 64 GB come to front which takes nearly one third (10,353) and 14 percent (4,510) of the total sales (33,303), respectively. Besides, over the time period analyzed, 19 percent of total offers (138,356) made for 24 smartphone models on the platform is for Apple iPhone

8 64 GB (26,082). Thus, these three products are selected for such an analysis. Each of them are observed through transactions of top seller of the product (ranked first in terms of total sales amount) and with respect to the market in Sections 1.1 and 1.2, respectively.

After determination of data parts to be analyzed, some key parameters are needed to construct 2SLS regression models. All of them are daily values so analysis is made accordingly. Sales quantity of the product and its price are main variables in the models. Moreover, number of sellers of the product is a significant information and may reflect a time effect as well as the USD exchange rate is expected to have a major impact on the sales of these products which are imported from abroad. Besides, since availability of a product is essential for a seller to be able to sell it, stock levels of sellers is expected to significantly affect the sales as well as the prices offered for a product on the platform. Thus, proportion of sellers without any stock for the product is another useful information. Similarly, the platform owner where these smart phones are sold may give promotions jointly with some sellers for reducing prices of their products. Therefore, since such a discount would be significant for sales numbers, this proportion of sellers who have this price reduction also seems valuable. Also, price information from another category on the platform may show some overall trend about the platform but will not be directly correlated with smart phone sales. In this manner, average daily prices offered for dishwashing machines on the same online platform can be useful, as well. Lastly, there is a double 11 campaign on November, 11 and its impact is not avoidable since it multiplies the sales on that day and it is thought that even the days before and after are also affected.

Note that in models built up from a market overview, these values are all daily averages including all sellers and the sales amount is a daily sum. However, when a seller's perspective is considered, there are the seller's daily sales quantity and price offered. Also, in such models, number of sellers of the product, proportion of sellers without any stock and ratio of the ones with reduced prices jointly with the platform are calculated without considering the seller himself/herself. Additionally, such models

analyzing a single seller, whether or not making a discount with the support of the platform on that day is another information used. All these features are listed in Table 4.1 with variable notations, descriptions and their value class.

Table 4.1. Variables Included in the Study.

Notation	Description	Class
$sumquantity_{jt}$	Total sales of product j on day t	Numeric
$sellerquantity_{ijt}$	Total sales of product j by seller i on day t	Numeric
$marketprice_{jt}$	Average price offered for product j on day t	Numeric
$sellerprice_{ijt}$	Average price offered by seller i for product j on day t	Numeric
$numberofsellers_{jt}$	Number of sellers of product j on day t	Numeric
$numberofcompetitors_{ijt}$	Number of sellers of product j except seller i on day t	Numeric
$stockouts_{jt}$	Proportion of sellers without any stock of product j on day t	Numeric
$stockouts_{(-i)jt}$	Proportion of sellers without any stock of product j except seller i on day t	Numeric
$plfdiscounts_{jt}$	Proportion of sellers with joint discount on product j on day t	Numeric
$plfdiscounts_{(-i)jt}$	Proportion of sellers with joint discount on product j except seller i on day t	Numeric
$sellerplfdiscount_{ijt}$	Availability of a joint discount on product j by seller i on day t	Logical
$dwmeanprice_t$	Average price offered for dishwashing machines on day t	Numeric
usd_t	USD/TL exchange rate on day t	Numeric

Table 4.1. Variables Included in the Study (cont.).

$d11_t$	Existence of double 11 campaign on day t	Logical
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An additional note is that 2SLS regression models which are shown in Sections 4.1 and 4.2 are all analyzed over a time horizon when the seller puts a price for the product on the platform (for market overview models, when at least one seller has a price for the product). It means days included in models are the ones sellers are willing to sell the product but it may not be resulted with a sales. Thus, since models include the price information of unsuccessful sales, following results will show sharp price sensitivities.

This chapter includes several 2SLS regression models built up through analysis of different products and sellers to observe the relationship between a product's price and its sales quantity. These models are determined through numerous model trials and their analysis. Many models are constructed involving combinations of above specified features (variables) for each one of determined products both from seller and market overview. Only models which can describe the target relationship significantly are shown. IV selection process and results of each model are shared as well.

4.1. Top Seller Analysis

The price and quantity relationship as well as effects of some other features on sales quantity are aimed to be observed. Models will be formed over products described in Chapter 3 , both from seller's perspective and market overview. Initially, seller specific constructed models are introduced.

Firstly, iPhone 8 64 GB which has nearly 20 percent of total number of offers made during that period on the platform is analyzed. To have a seller specific perspective, a seller should be determined and the selection parameter here is not surprisingly sales

volume of each seller. The seller with id 2070783 sold 2161 smart phones of iPhone 8 64 GB, which is 63 percent of total sales quantity of this product, so he/she dominates the market very significantly. Therefore, the sales transaction data of the seller 2070783 for iPhone 8 64 GB is analyzed on a daily basis through the 2SLS regression model.

Before the analysis, the last step is the determination of IV and control variables. Note that the outcome is daily total quantity sold by the seller and the endogenous variable is the average daily price offered by him/her for iPhone 8 64 GB.

The double 11 campaign (occurs on November, 11) has an unavoidable impact since it multiplies the sales quantity on that day and its effect can be seen before and after, as well. Moreover, whether or not making a discount with the support of the platform can be also important on a seller's daily sales amount. Both factors are controls in the model.

To obtain the IV is a much harder task. To test the validity of an IV, initially each candidate instrumental variable can be put in a first stage regression model where the outcome is price and the IV candidate is the predictor so it is expected to observe significance. Then, in the case of observing statistical significance of the IV candidate for price, the candidate is now put as the only IV into the second stage model where the outcome is quantity sold. Thus, a good model is aimed which can describe the relationship between the product's price and its sales amount. In other words, it is tested that firstly the IV is correlated with the price and then a fit model represents the price-quantity relationship is expected through using each single IV candidate.

Since it may show some overall trend, average daily prices offered for dishwashing machines, a totally unrelated category on the same online platform can be a good IV. Similarly, number of sellers of iPhone 8 64 GB as a proxy to strength of competition can be used as an IV. Also, the exchange currency of US dollar to Turkish lira has an impact on prices offered but not directly affecting the quantity which is a signal to be a candidate IV. Therefore, these three are tested through the methodology described

above. Besides, correlation matrix for all described features considered to be put in the model (IV candidates, controls, endogenous variable and outcome) is shown in Table 4.2. Note that these results are obtained from sales transactions data of Seller 2070783 for Apple iPhone 8 64 GB as well as correlation for existence of a double 11 campaign and joint discount with the platform could not be obtained since they are logical values.

Table 4.2. Correlation Matrix for Apple iPhone 8 Top Seller Model.

	seller quantity	seller price	dwmean price	numberof competitors	usd
seller quantity	1	-0.117	-0.053	0.116	-0.060
seller price		1	0.720	-0.832	0.326
dwmean price			1	-0.571	0.368
numberof competitors				1	-0.097
usd					1

Firstly, all of three variables (dwmeanprice, numberofcompetitors, usd) are put in OLS regression where the seller price is the outcome and each variable is individually predictor. Here, the aim is to observe any correlation between each instrument candidate and price (see Table A.1).

Due to the observed correlation between instrument candidates and seller's price, 2SLS regression models are formed with quantity sold as the outcome and both existence of a joint discount with the platform (sellerplfdiscount) and the double 11 campaign (d11) are put as controls. Separate models are formed including each candidate as single IV for price to see dynamics with the quantity while avoiding simultaneous causality effect. Table 4.3 shows related results. In each model, seller's price, joint discount with platform and double 11 campaign are found statistically significant. Moreover, all of instrument candidates pass diagnostic tests so it is obtained that they

are good IVs (see Table B.1).

Table 4.3. iPhone 8 Top Seller 2SLS Regression Results for IV Selection.

	<i>Dependent variable: sellerquantity</i>		
log(sellerprice)	−22.554*** (4.860)	−24.241*** (4.596)	−28.545*** (10.064)
sellerplfdiscount	3.477*** (0.823)	3.406*** (0.819)	3.227*** (0.899)
d11	463.752*** (5.316)	463.635*** (5.305)	463.335*** (5.330)
Constant	192.558*** (41.356)	206.913*** (39.109)	243.529*** (85.621)
IV	dwmeanprice	numberofcompetitors	usd
Observations	376	376	376
Adjusted R ²	0.954	0.954	0.954
Residual Std. Error (df = 372)	5.253	5.244	5.232
<i>Note: *p<0.1; **p<0.05; ***p<0.01, Each model has single IV as dwmeanprice, numberofcompetitors and usd, respectively. Robust errors in paranthesis</i>			

Since all three variables are statistically correlated with the price and forms good models individually with the quantity (i.e. passing all IV tests meaning they are strong and price is an endogenous variable), the second stage regression including all three as IVs is defined as $sellerquantity_{ijt} = \alpha_t + \beta_1 \log(sellerprice)_{ijt} + \beta_2 sellerplfdiscount_{ijt} + \beta_3 d11_t + \varepsilon_t$ where $sellerquantity_{ijt}$ is the outcome, $sellerprice_{ijt}$ is the endogenous variable,

$dwmeanprice_t$, $numberofsellers_{(-i)jt}$ and usd_t are instrumental variables as well as $d11_t$ and $sellerplfdiscount_{ijt}$ are controls. ε_t describes unobserved shocks on day t which may affect the sales quantity of the product by its seller. This can be any condition of that day like the weather, existence of a special event(e.g., mother's day),

status of internet access and so on. Note that all of them are daily values (t denotes day and $t=1:376$).

In Table 4.4 Columns designated with (1), results and the analysis of the model are shown. It gives the unbiased estimator of the casual effect of price on sales amount. The negative impact of price as well as positive effects of double 11 campaign (significantly high) and seller's joint discount with the platform on the amount sold can be observed. Note that all are statistically significant. It is understood that when the seller increase its price by one percent on average, daily total sales quantity is expected to decrease by 24. In the same manner, when seller has a joint discount on the product, sales amount increases by approximately 3.5 and if there is double 11 campaign, this rise in quantity sold is likely 150 times higher.

Table 4.4. Apple iPhone 8 Top Seller Results.

	<i>Dependent variable: sellerquantity</i>		
	(1)	(2)	(3)
log(sellerprice)	-24.031*** (4.146)	-29.133*** (3.822)	-21.519*** (5.223)
sellerplfdiscount	3.415*** (0.815)	3.202*** (0.811)	2.551 (1.703)
d11	463.649*** (5.305)	463.294*** (5.291)	461.819*** (5.948)
Constant	205.122*** (35.275)	248.527*** (32.527)	185.759*** (44.425)
IV	dwmeanprice numberofcompetitors usd	-	dwmeanprice numberofcompetitors usd
Observations	376	376	272
Adjusted R ²	0.954	0.955	0.960
Residual Std. Error	5.245 (df = 372)	5.175 (df = 369)	5.706 (df = 268)
Weak instruments	722.866***	-	542.642***
Durbin-Wu-Hausman	10.715**	-	2.323
Sargan	0.584	-	2.401
<i>Note:</i> (1) 2SLS model results over 376 days with three IVs as dwmeanprice, numberofcompetitors and usd, (2) OLS model results over 376 days, (3) 2SLS model results over 272 days considering only sales,			
<i>Note:</i> Robust errors in paranthesis for (1) and (3),			
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01			

Moreover, there are three diagnostic tests which measure the success of IVs and the results are in Table 4.4. Firstly, rejecting Weak Instruments test states there is high correlation between IVs and the endogenous variable (here, product's price).

Secondly, if Durbin-Wu-Hausman is rejected as well, then IVs are less correlated with the outcome (in this model, amount sold). Lastly, the Sargan test is used to check whether there is excess usage of instruments (ie. that can be excluded from the model without disturbing its fitness). Since it is not rejected, it means all of these three IV variables should be included in the model. As an outcome, these results show the goodness of our IV selections as well as the 2SLS regression model.

Additionally, the results should be compared against the OLS regression model (without IV values). As it is given in Table 4.4 (2), all of three factors (seller's price, availability of joint discount with the platform and existence of double 11 campaign) are again statistically significant for the sales amount of the product. However, although seller's joint discount and the double 11 campaign have similar affects on quantity, one can observe a higher impact of product's price on the sales amount. This additional nearly 5 times of log of change in price is caused by simultaneous bias which is avoided through the 2SLS model.

On the other hand, further analysis is made considering only sales transactions, i.e., days with no sales are excluded. It is known that information of products not sold (most importantly its price) is valuable and may change the output of the analysis. (Bijmolt et al., 2005) Table 4.4 (3) shows the result of the model constructed with only sales data over 272 days. The increase (nearly 3) in price coefficient can be considered as selection bias due to only having sales information. More importantly, having a platform discount is no more statistically significant. This may conclude that sales are made with discounted prices so the model with only sales data could not statistically find this information significant. Lastly, this 2SLS model over 272 days could not pass the Durbin-Wu-Hausman test with IVs as daily average price of dishwashing machines, number of competitors and USD/TL exchange rate. All these three points, slight change in price coefficient, having platform discount appearing statistically non-significant and selected IVs having endogeneity problems refer to the selection bias where it is fixed with the valuable information of products could not be sold.

4.2. Market Analysis

Now that the dynamics of price and quantity relationship for top sellers of listed products are analyzed in Section 4.1, what about the market analysis? Are features of a product effective on its sales quantity like in Section 4.1? What are the instrumental variables and controls?

To investigate the price-quantity relationship from market overview, it is beneficial to observe each single smart phone models separately since they have unique market dynamics due to different factors like competition levels, brand reputation, consumer behaviours. Huawei P20 Lite 64 GB comes in the second place in terms of total revenue (22.2 million Turkish Liras) just after Apple iPhone 8 64 GB (25.7 million Turkish Liras which is analyzed in section 4.1. So, it is selected as a good representative for such markets on online platforms. There are 8147 transactions of the specified smart phone over 376 days and 10,353 are sold by 41 sellers on the platform. Here, the link between the daily total number of products sold and the daily average market price offered is aimed to be obtained through 376 observations. Again, due to the simultaneity bias specified above, 2SLS model is constructed.

Proportion of sellers who reduced their prices jointly with the platform on a daily basis ($plfdiscounts$) is thought to be an IV candidate since it may affect competition on the platform so this can affect market prices directly. It is known that double 11 (d11) campaign is unavoidable so again it should be control. On the other hand, when the relationship between price and quantity on a market basis is thought, availability of the product, i.e. simply the stock level, may be significant. So, ratio of sellers without any stock of the product on a daily basis should be controlled, as well. Thus, it is another control variable in the model. Correlations between these variables of Huawei P20 Lite 64 GB market are listed in Table 4.5.

Table 4.5. Correlation Matrix for Huawei P20 Market Model.

	totalquantity	marketprice	plfdiscounts	stockouts
totalquantity	1	0.081	0.007	-0.146
marketprice		1	0.017	-0.541
plfdiscounts			1	-0.542
stockouts				1

A surprising result is seen as there is a positive correlation between daily total quantity sold and daily market price. As well as the fact that it is very slightly positive and afterwards it will be shown that the sign of price in models will be negative (as expected), this may happen due to some time effect. People may continue to buy a smart phone more despite increasing prices which may be caused by the raise in currency rate. Also, there exists a very small correlation between the daily average market price and proportion of sellers who have platform discount. Since that proportion is argued that it is effective for price and so used as an IV, this may be a question. However, results taken from the first stage regression supports the argument so the IV selection. Moreover, a negative correlation between the daily average price of a product and the ratio of stock-out sellers is interesting as well. This may be caused by release of the newer product (model) so sellers may not want to sell the old one and try to diminish their stocks with cheaper prices.

It is assumed that the IV candidate (*plfdiscounts*) does not have an independent effect on quantity. It is expected to successfully estimate the average market price in the model so firstly, relationship between each instrument candidate and average market price is observed (see Table A.2). Statistically significant good results for that relationship leads to determine the second stage regression as $totalquantity_{jt} = \alpha_t + \beta_1 \log(marketprice)_{jt} + \beta_2 stockouts_{jt} + \beta_3 d11_t + \varepsilon_t$ where $totalquantity_{jt}$ is the outcome, $marketprice_{jt}$ is the endogenous variable, $plfdiscounts_{jt}$ is instrumental variable as well as $stockouts_{jt}$ and $d11_t$ are controls. ε_t describes unobserved shocks on day t which may affect the sales amount of the product on the platform. Note that again all

of them are daily values (t denotes day and $t=1:376$).

The results are given in Table 4.6 (1). It is observed that both price and availability of the product are statistically significant for sales. A rise of price by one percent on daily market average decreases the total daily quantity sold by over 114 times. Similarly, when more sellers are left without any stock of the product on a day, daily sales amount reduces. For example, when the ratio of stock-out sellers increased by 0.1, it leads to a decrease in total quantity by over 9 on a daily basis. On the other hand, again the double 11 campaign has still a very dominant positive effect.

Table 4.6. Huawei P20 Lite Market Results.

	<i>Dependent variable: totalquantity</i>		
	(1)	(2)	(3)
log(marketprice)	-114.123*** (25.059)	-52.864*** (9.776)	-123.923*** (26.670)
stockouts	-92.476*** (9.172)	-73.206*** (5.418)	-103.984*** (14.923)
d11	1,884.668*** (17.095)	1,879.555*** (16.157)	1884.929*** (18.711)
Constant	945.897*** (198.065)	461.729*** (77.290)	1025.847*** (211.481)
IV	plfdiscoun	-	plfdiscoun
Observations	376	376	321
Adjusted R ²	0.971	0.974	0.970
Residual Std. Error	16.930 (df = 372)	16.101 (df = 372)	18.547 (df = 317)
Weak instruments	75.257***	-	69.965***
Durbin-Wu-Hausman	8.095**	-	9.845**
<p><i>Note:</i> (1) 2SLS model results over 376 days with single IV as plfdiscoun</p> <p>(2) OLS model results over 376 days, (3) 2SLS model results over 321 days considering only sales,</p> <p><i>Note:</i> Robust errors in paranthesis for (1) and (3),</p> <p><i>Note:</i> *p<0.1; **p<0.05; ***p<0.01</p>			

Additionally, the diagnostic test results for IVs in the second stage regression of 2SLS are shown in Table 4.6. P-values are less than 0.001 and nearly 0.005 for Weak instruments and Durbin-Wu-Hausman tests, respectively. It means ratio of sellers offering a joint discount with platform is significantly correlated with the average market price but not with the total quantity. Note that Sargan test does not give any result since there is a single IV.

Similarly, if this model is formed as OLS without an IV, then the results will be as it is stated in Table 4.6 (2). An increase in daily average market price will cause less than a half reduction in daily total sales quantity due to the simultaneity bias. Thus the bias of OLS in price elasticity is corrected. Moreover, this change also weakens the possible decrease in quantity caused by the increase in the proportion of sellers without any stock on that day.

Moreover, to show how the selection bias is fixed, Table 4.6 (3) has model results over 321 days with at least one product could be sold in total. One can see slight changes in coefficients of endogenous variable (average market price) as well as controls (proportion of stock-out sellers and double 11 campaign effect) and the constant value which determines the amount of sales if there is zero price. Critical difference is the bias of additional decrease in quantity of nearly 9 in case of an one percent increase in price. Similarly, when on a day the ratio of stock-out sellers increase by 0.1, a biased decrease of over 10 (instead of 9) in total quantity appeared without information of products could not be sold.

Also, note that this 2SLS regression model is constructed with adjusted prices where daily average market prices are divided by CPI (Consumer Price Index) values that are announced monthly. There is only a slight difference in coefficients. (see Table C.1)

Although a market analysis is made to observe the quantity-price relationship of a smart phone sold on an online platform, one can wonder what happens when another product is analyzed (i.e. is the result obtained product specific). Thus, to be able to know more about the dynamics of sales of smart phones on the online platform, Apple iPhone 8 Plus 64 GB which takes second place after Huawei P20 Lite 64 GB in terms of sales amount can be analyzed. It is sold 4,510 times over 376 days by 73 different sellers on the platform.

To obtain a good model which statistically explains the relationship with the

sales amount and estimates the price well, ratio of sellers having joint discount with the platform (*plfdiscounts*) on a daily basis is an IV candidate in a similar manner. Besides, double 11 campaign (*d11*) is the control not surprisingly. Correlation matrix of these specified features for Apple iPhone 8 Plus 64 GB is shown in Table 4.7. Note that daily ratio of sellers without any stock (*stockouts*) is also included since a further analysis will be made for this product over this information.

Table 4.7. Correlation Matrix for Apple iPhone 8 Plus Market Model.

	totalquantity	marketprice	plfdiscounts	stockouts
totalquantity	1	0.048	0.054	-0.137
marketprice		1	-0.331	-0.040
plfdiscounts			1	-0.426
stockouts				1

Here again, there is a very small positive correlation observed between quantity and price. The explanation made for the similar situation seen in the market analysis of Huawei P20 should be remembered. Also, the correlation between the daily market price and IV candidate *plfdiscounts* should be noted to support the Iv selection.

Same steps are taken for consideration of IV candidate and it is observed that proportion of sellers with a joint discount is statistically significant for average market price on a daily basis for Apple iPhone 8 Plus 64 GB. (see Table A.3) Thus, the second stage regression is $totalquantity_{jt} = \alpha_t + \beta_1 \log(marketprice)_{jt} + \beta_2 d11_t + \varepsilon_t$ where outcome and endogenous variable are unchanged and $d11_t$ is the control as well as $plfdiscounts_{jt}$ is instrumental variable. ε_t represents the unobserved factors affecting the sales quantity of the product throughout the market.

Table 4.8 shows results regarding this regression. One can observe that the existence of the double 11 campaign causes a very large increase on the daily total quantity

whereas an opposite effect of price is seen and much higher rather than previously mentioned seller and market models (Apple iPhone 8 64 GB and Huawei P20 Lite 64 GB).

Table 4.8. Apple iPhone 8 Plus Market Results.

	<i>Dependent variable: totalquantity</i>		
	(1)	(2)	(3)
log(marketprice)	−223.901*** (74.480)	49.077** (21.091)	−175.234** (73.211)
d11	391.373*** (16.077)	395.863*** (13.321)	390.984*** (15.601)
Constant	1,967.319*** (650.780)	−417.872** (184.286)	1,543.270*** (639.676)
IV	plfdiscunts	-	plfdiscunts
Observations	376	376	338
Adjusted R ²	0.568	0.702	0.624
Residual Std. Error	16.009 (df = 373)	13.299 (df = 373)	15.533 (df = 335)
Weak instruments	49.04***	-	44.58***
Durbin-Wu-Hausman	23.34***	-	15.36***
<p><i>Note:</i> (1) 2SLS model results over 376 days with single IV as plfdiscunts, (2) OLS model results over 376 days, (3) 2SLS model results over 338 days considering only sales, <i>Note:</i> Robust errors in paranthesis for (1) and (3), <i>Note:</i> *p<0.1; **p<0.05; ***p<0.01</p>			

Also, again note that rejecting Weak instruments and Durbin-Wu-Hausman tests with p-values less than 0.001 argues that IV is strong and endogenous in the model. Again, Sargan test cannot be checked due to having a single IV.

Moreover, these results point out the effect of simultaneity bias and how 2SLS approach solves the problem very significantly. 2SLS model (Table 4.8 Column 1) states that an increase of one percent on daily average price offered for the product makes the sales amount go down as much as over 223. On the other hand, if the daily market price is not estimated through proportion of sellers with a joint discount on a day, i.e, the OLS model (Table 4.8 Column 2), a positive effect of price on quantity occurs which changes the observation very significantly. Therefore, again this corrects the bias in price elasticity. Likely, due to selection bias, 2SLS regression over 338 days with sales (Table 4.8 Column 3) shows relatively smaller effect of price on the quantity and this is fixed through using the information of products could not be sold.

To be able to observe the impact of stocks of sellers, since availability of product alternatives is important, the second stage regression is $totalquantity_{jt} = \alpha_t + \beta_1 \log(marketprice)_{jt} + \beta_2 stockouts_{jt} + \beta_3 d11_t + \varepsilon_t$ just as the one for Huawei P20 Lite 64 GB market analysis with two controls as $stockouts_{jt}$ and $d11_t$ and the same IV which is $plfdiscounts_{jt}$.

Results are stated in Table 4.9. Firstly, note that results are almost the same for the double 11 campaign. However, it is observed that proportion of stock-out sellers is statistically significant for sales quantity and there is a negative effect. Here, negative impact of market price is cropped so if the product is presented one percent more expensive, its sales amount is expected to decrease by nearly 117 in daily total. Also, when more sellers are left without any stock on a day, total sales amount decrease again. It is like if this ratio increases by 0.1, then daily total quantity decrease by nearly 3. Note that selecting daily proportion of sellers given a discount by the platform passes the Weak instruments and Durbin-Wu-Hausman tests.

Table 4.9. Apple iPhone 8 Plus Market Results with Stock-out Ratio.

	<i>Dependent variable: totalquantity</i>		
	(1)	(2)	(3)
log(marketprice)	-116.716** (56.851)	46.355** (20.723)	-102.695** (58.787)
stockouts	-28.755*** (7.572)	-26.877*** (6.988)	-22.775*** (8.178)
d11	391.296*** (14.165)	394.099*** (13.089)	390.872*** (14.385)
Constant	1,042.617** (497.022)	-383.023** (181.197)	918.680* (514.114)
IV	plfdiscouts	-	plfdiscouts
Observations	376	376	338
Adjusted R ²	0.665	0.713	0.681
Residual Std. Error	14.105 (df = 372)	13.060 (df = 372)	14.321 (df = 334)
Weak instruments	68.23***	-	61.41***
Durbin-Wu-Hausman	11.68***	-	9.49**
<i>Note:</i> (1) 2SLS model results over 376 days with single IV as plfdiscouts, (2) OLS model results over 376 days, (3) 2SLS model results over 338 days considering only sales,			
<i>Note:</i> Robust errors in paranthesis for (1) and (3),			
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01			

Again, 2SLS and OLS regressions (Table 4.9 Columns 1 and 2, respectively) give significantly different outcomes (even the sign) regarding the impact of market price on sales quantity due to simultaneous causality. Also, due to selection bias (seen in Table 4.9 Column 3), a smaller effect of both daily price and proportion of stock-out sellers appears when only sales data is considered. An additional note is that this selection bias also slightly effects the endogeneity (Durbin-Wu-Hausman has higher

p-value) of instrumental variable as the proportion of sellers with platform discount.

4.3. Predictions

After obtaining statistically significant parametric models which can describe the price-quantity relationship by avoiding simultaneity bias through instrumental variable approach, one can use the models for prediction. Thus, this section aims to test the predictive power of those statistically significant descriptive models.

A product's cycle is considered (some products may have no sales through the end of time period observed) and a division is made over it as train and test sets. Predictions are made in two consecutive stages as initially a 2SLS regression model is formed over the train data with IVs and then prediction is made through that model and the test data.

Firstly, recall the 2SLS regression model constructed to observe market dynamics of Huawei P20 Lite 64 GB over 376 days as $totalquantity_{jt} = \alpha_t + \beta_1 \log(marketprice)_{jt} + \beta_2 stockouts_{jt} + \beta_3 d11_t + \varepsilon_t$ where $totalquantity_{jt}$ is the outcome, $marketprice_{jt}$ is the endogenous variable, $plfdiscounts_{jt}$ is instrumental variable as well as $stockouts_{jt}$ and $d11_t$ are controls.

When transactions are observed for the above mentioned product, after 320 days, there is nearly zero sales. Thus, it will be more meaningful to make a test and train sets division over this time period. Hence, firstly the model is constructed over 290 days and the results are given in Table 4.10.

Table 4.10. Huawei P20 Market Prediction with Training Data.

	<i>Dependent variable: totalquantity</i>
log(marketprice)	−101.31*** (22.74)
stockouts	−51.26*** (15.37)
d11	391.405*** (16.447)
Constant	835.01*** (179.14)
Observations	290
Adjusted R ²	0.9737
Residual Std. Error	18.12 (df = 286)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01, plfdiscounst is IV, Robust errors in paranthesis	

Initial prediction is made for Huawei P20 Lite 64 GB over the train set data (290 days) and the above specified model. Then, the test data is the last 30 days of the product's life (i.e., before total daily sales become zero) which is between days 291 and 320. Same model is used with parameters of the test data (30 days). One should check the validity of these predictions, so accuracy measures are observed which are obtained through comparison of predicted total daily quantities and the (real) values in the data. Those accuracy results are given in Table 4.11

Among these measures, Mean Error of in-sample prediction is a generic term to evaluate the predictive power of the model (Column 1). Here, the error is nearly zero. Moreover, by using these measures, one may compare in-sample and out-of-sample predictions and should expect to have lower errors for in-sample. The results show that Mean Error and Mean Percentage Error (as statistically good signals) are much lower when an in-sample prediction is made rather than out-of-sample.

Table 4.11. Accuracy Measures of Prediction - Huawei P20.

Measure	Result		
	1	2	3
Mean Error	2.904e-12	21.259	-0.844
Root Mean Squared Error	17.999	22.270	16.890
Mean Absolute Error	13.645	21.257	13.190
Mean Percentage Error	4.250	67.991	15.999
Mean Absolute Percentage Error	59.469	67.991	74.140
<i>Note:</i> Results of (1) in-sample prediction over 290 days, (2) out-of-sample prediction over 30 days as test data (the train data is 290 days) and (3) average of accuracy measures of ten samples of 30 days within 290 days.			

Besides, same accuracy measures are obtained through the comparison of predicted and actual daily total quantities of randomly selected 30 days (same length with the test data) within 290 days (train set). This sampling aims to show how dependent the accuracy measures on the data itself (length or the actual values). In Column 3, one can see the average result of each measure as a result of applying the similar methodology over ten samples of 30 days. Note that the data excluding each sample set is used to form independent regression models for all predictions through sampling. 30 days are randomly selected from the data and they do not need to be consecutive days.

Thus, firstly, through comparing results in Columns 1 and 3 in-sample prediction seems to be much better due to being over-fit and secondly, the difference between Columns 2 and 3 signals the effect of data selection where lengths are the same but the data is different.

Recall the second stage of 2SLS regression model obtained over the transaction data of Apple iPhone 8 Plus 64 GB from the market overview over 376 days as $\text{totalquantity}_{jt} = \alpha_t + \beta_1 \log(\text{marketprice})_{jt} + \beta_2 d11_t + \varepsilon_t$ where outcome and en-

ogenous variable are unchanged and $d11_t$ is the control as well as $plfdiscounst_{jt}$ is instrumental variable. ε_t represents the unobserved factors affecting the sales quantity of the product throughout the market.

Again, train and test division is needed over the time period observed. Train set is set as the first 346 days of 376 days leaving the remaining 30 days for test data and the model results are given in Table 4.12.

Table 4.12. Apple iPhone 8 Plus Market Prediction with Training Data.

	<i>Dependent variable: totalquantity</i>
log(marketprice)	-221.723*** (61.839)
d11	391.405*** (16.447)
Constant	1,948.291*** (540.268)
Observations	346
Adjusted R ²	0.579
Residual Std. Error	16.396 (df = 343)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01, plfdiscounst is IV, Robust errors in paranthesis	

Firstly, the above specified model is used to make an in-sample prediction for the daily total quantity sold of Apple iPhone 8 64 GB for the train set (346 days). Then, the test data is taken as the last 30 days of the total time horizon and out-of-sample prediction is made through this model and predictors taken from the test set (30 days). To check the validity of these predictions, accuracy measures are observed which are obtained through comparison of predicted total daily quantities and the (real) values in the data. Those accuracy results are given in Table 4.13

Table 4.13. Accuracy Measures of Prediction - Apple iPhone 8 Plus.

Measure	Result		
	1	2	3
Mean Error	7.24e-12	0.057	-16.672
Root Mean Squared Error	16.324	9.867	33.410
Mean Absolute Error	10.855	8.646	25.193
Mean Percentage Error	73.052	-240.287	170.910
Mean Absolute Percentage Error	172.128	320.030	931.500
<i>Note:</i> Results of (1) in-sample prediction over 290 days, (2) out-of-sample prediction over 30 days as test data (the train data is 290 days) and (3) average of accuracy measures of ten samples of 30 days within 290 days.			

Here, again one can use these measures to evaluate the predictive power of the model as well as to compare two predictions. Likely, in-sample prediction has a nearly zero Mean Error which signals a statistically good predictive model. Also, the results show that Mean Error as well as Mean Percentage Error are lower for in-sample prediction when compared with out-of-sample prediction results.

Also, again prediction is made through sampling over the train set. Column 3 represents average measures of ten different predictions over randomly selected 30 days. Results obtained are not good and proves the goodness of in-sample prediction is resulted by being over-fitting. Meanwhile, the data selection seems effective on the prediction accuracy when the results in Columns 2 and 3 are compared.

These prediction results and accuracy measures are listed to argue the predictive power of those models which are discussed with their descriptive strengths in Chapter 4. In Chapter 4, 2SLS models are constructed to observe price-quantity relationship and the data over 376 days are fully analyzed to have a good fit models. However, for these predictions, train and test division is made to have both in-sample and out-of-

sample results. These predictions follows a methodology as firstly determination of the model parameters through 2SLS regression models over train data and then usage of the information of those parameters from the train or test data (i.e. in-sample or out-of-sample). Thus, it results in predicted quantity values for those data sets.

Platform owners may come up with and use such predictions since they have full information. Model parameters may be set through observing a time period on the platform and then discover quantities sold in the future with changing these parameters in different scenarios. They can benefit from such a methodology to find out possible quantities for changing prices, exchange rates. Likely, they may see the possible change in sales amount through changing proportion of sellers with platform discount and then make these decisions accordingly.

5. CONSUMER CHOICE MODELS

The relationship between quantity and price is investigated along with some other attributes related with stock levels, discounts, number of sellers etc. The parametric regression models could show some insights from sellers' perspective as well as market overview on an online platform in this sense. Now, this can be observed and analyzed from the buyer's side.

Customer choice models may help to understand the consumer behavior in purchasing a product. Questions like which factors affecting their decision process before making a purchase. For instance, through such models, for the comparison among product alternatives, which product attributes and/or seller information that are considered by the customer may be observed. Thus, customers' decision making mechanisms can be analyzed to search for the factors affecting the market dynamics, especially price and quantity.

Main purpose is to observe the online market dynamics for smart phones from a customer's perspective and discover the factors affecting consumer decision mechanism and buying behaviour. What is behind a customer's purchase (product's price, its seller, some other features like brand reputation, stock level etc.) and how much effective these are will be answered. Moreover, further developments will be made over initially constructed model to get answers related with customer's attitude in selecting a product (i.e., multi-step decision mechanisms will be modelled).

5.1. Processing Data and Assumptions

Choice models in this chapter are formed through analysis of market data described in Chapter 3. For the sake of analysis, a narrower competitive environment is assumed while constructing consumer choice models. To save the significant information that will actually show the behavior in the market, the reduced data includes

three top sellers with highest sales amount and two prominent smart phone models which lead the market. Apple iPhone 8 64 GB (afterwards it will be called as Product 1) is the leader with 26082 transactions which is over 18 percent of the total number by all of the 24 different smart phone models on the platform. It is selected with its main competitor Samsung Galaxy S8 64 GB (from now on, it is Product 2). Then, top sellers of these smart phones are considered but of course, to provide a fair comparison, it is watched out that such sellers should offer both of these products. Therefore, sellers with ids 147353, 2070783 and 329366 are selected (instead of seller ids, they will be called as Sellers 1,2 and 3, respectively). Their sales information is given in Table 5.1.

Table 5.1. Number of Sales over 376 days.

	Product 1	Product 2
Seller 1	2161	526
Seller 2	501	35
Seller 3	67	380

Finally, 46 days when both two products are presented for sale by all of three sellers on the platform are determined since all alternatives (seller-product combinations) should always be present to a customer to ensure the consistency of the choice model. This significant section of the data is a strong representative which describes the competition through focusing on the transactions dominating the market. The data cleaning here is made through filtering days when the sale status of three sellers for two products are "On-Sale", meaning they all have stocks to sell each product.

It is assumed that customers are exposed to these two products by three sellers during the day, and choose one of them to buy. Although it cannot be observed whether this is the precise consumer behavior on the platform, it is thought to be an accurate description of choice behavior.

5.2. Multinomial Logit Model

Multinomial logit (MNL) model is formed to observe consumer behavior in choosing a product among alternatives (Train, 2009, p. 38). Due to the existence of two products (Products 1 and 2) and three sellers (Sellers 1,2 and 3), a total of six alternatives are available for the consumer on a daily basis.

Through this consumer choice model, it is aimed to understand dynamics of customer behaviour in purchasing decision and its implications on market demand. The decision mechanism behind making a selection among different buying options for the same product will be observed. In other words, monopsony (where there is one buyer and many sellers, i.e. buyer's monopoly market dynamics is aimed to be analyzed. It will be shown which parameters are statistically significant for a customer and how effective they are on his/her choices.

Each alternative has its own attributes as the price of the product offered by the seller and the proportion of the ones who are out of stock among other sellers of that product except the seller itself. Moreover, number of sellers of the product on that day and the average price offered by rest of the market except the alternatives are added to the model. Note that all values are daily. To ensure clarity, going through an example can help. Small part of the data which describes an example of such selection on 09/12/2018 is given in Table 5.2. Firstly, one can observe that an alternative is chosen among others, i.e., a customer buys Product 1 from Seller 2 (alternative Product1Seller1) after comparing it with other five alternatives listed. Here, for the chosen alternative on 09/12/2018, the price offered by the seller is 4292 Turkish Liras as well as the proportion of Product 1 sellers without any stock is 0.161 (except Seller 1). Moreover, the market price of that product (ie. average price offered for Product 1 by others besides Sellers 1,2 and 3) is 5327 Turkish Liras and number of Product 1 sellers is 56 on the same day.

Table 5.2. Part of the Data as a Single Consumer Choice.

Date	choice	alternative	seller price	stockout ratio	numberof sellers	market price
09/12/2018	FALSE	Product1Seller1	4379.9	0.161	56	5327.1
09/12/2018	TRUE	Product1Seller2	4292.0	0.161	56	5327.1
09/12/2018	FALSE	Product1Seller3	4749.0	0.161	56	5327.1
09/12/2018	FALSE	Product2Seller1	3178.9	0.120	25	3596.8
09/12/2018	FALSE	Product2Seller2	3119.0	0.120	25	3596.8
09/12/2018	FALSE	Product2Seller3	3199.0	0.120	25	3596.8

In other words, it is assumed that when a customer enters the platform, he/she sees six alternatives (product-seller combinations) and is able to observe prices offered by each one of them (**sellerprice**), the proportion of sellers without any stock except the seller (**stockoutratio**), market price besides the alternatives (**marketprice**) and number of sellers offering the product on that day (**numberofsellers**).

Consumer utility is $V_j = \beta'x_j$ and x_j is the vector of observed variables (price offered by the seller, proportion of sellers without any stock, number of sellers and average price in the rest of the market) relating to alternative j. Model outcome will be the probability of the customer choosing an alternative among others, calculated through division of consumer utility of selecting that alternative over sum of utilities of all choices.

Therefore, the model is $P_i = \int (\frac{e^{\beta'x_i}}{\sum_j e^{\beta'x_j}}) f(\beta) d\beta$ where P_i denotes the probability of the choice maker (the customer) selects alternative i (the product seller combinations) among all choices and consumer utility of choosing alternative j is $V_j = \beta'x_j$ as specified above.

MNL models may be evaluated with different values of β with weights given by

the density $f(\beta)$. In most applications, $f(\beta)$ is specified as continuous. (Train, 2009, p. 38)

Firstly, frequencies of alternatives are obtained from the model which actually show how many times an alternative is chosen, i.e., how many customers choose which alternative on the platform over the period observed. Table 5.3 shows the results. It is observed that customers visited the platform during that time period mostly bought Product 1 from Seller 2. The seller sold this product with an amount of 463 out of the total number of products sold which is 856. Thus, its frequency is 0.54 and one can say that 54 percent of customers visiting the platform over the specified time period choose that alternative among those six while considering the price offered, the proportion of sellers without any stock, number of sellers and market price besides those sellers.

Table 5.3. Frequencies of Alternatives.

Alternative	Number of Sales	Frequency
Product1Seller1	206	0.24
Product1Seller2	463	0.54
Product1Seller3	38	0.04
Product2Seller1	18	0.02
Product2Seller2	99	0.12
Product2Seller3	32	0.04
Total	856	1.00

The above specified model aims to estimate coefficients of observed factors on the consumer utility (β') as well as alternative specific constants (describes how each alternative affects customer's utility, e.g., seller's service quality and product reputation). The output of the multinomial logit model can be observed in Table 5.4 Column MNL. It includes coefficients for intercepts and variables. Intercepts represent alternative specific constant utilities and the values are given with respect to a base alternative so there are intercept values as much as one less than the number of choices. Here, buying

Product 1 from Seller 1 is the basis (i.e., its intercept can be taken as zero) and for instance the utility of buying the same product from Seller 2 is higher whereas buying the alternative product (Product 2) from the same seller (Seller 1) is lower. These differences may be caused by some factors that are not observable in the data. For example, Seller 2 may provide better service, faster delivery or has a higher reputation on the platform as well as Product 1 may be more popular than its competitor (i.e., brand reputation effect). Indeed, Seller 2 is a very active seller for this product as the rest of the data also shows. In general, it clearly appears that customers will gain more utility by purchasing Product 1 rather than its competitor. Moreover, among sellers, especially for Product 1, Seller 2 comes to front so buying from him/her has some additional utility to a customer. Also, buying Product 1 from Sellers 2 and 3 have important effects on a consumer due to the output of their constant utilities. In other words, sellers have statistically significant impacts on purchasing decision of Product 1 unlikely the alternative product.

It is obvious that in buying a product, price offered by the seller is significant for customers that they consider this before making a decision which is actually expected. On the other hand, number of sellers is not observable to them and it is put as a control in the model for the competition effect which is obtained as significant, too. Thus, the price customer sees as well as the competition between sellers affect the buying decision. It is observed that both price and competition have negative impacts on them. Availability of more sellers (increased competition) on the platform drops the choice probability by 0.222 which is more than the negative effect of an increase in product's price (0.012). This may not be guessed before the analysis that competition is more effective than the the price for customer behaviour. Increased alternatives may confuse customers or it can relax them to postpone their purchase thus may cause loss in sales. On the other hand, proportion of sellers without any stock and the average price offered by the rest of the market are not statistically significant for consumer choice.

Table 5.4. MNL Model Results.

	<i>MNL</i>	<i>Product Nest</i>	<i>Seller Nest</i>
	<i>Dependent variable: choice</i>		
Product1Seller2	0.569*** (0.087)	0.445*** (0.165)	0.390*** (0.136)
Product1Seller3	-0.794*** (0.185)	-0.669** (0.270)	-1.978*** (0.761)
Product2Seller1	-8.274 (9.981)	0.166 (11.005)	5.704 (17.505)
Product2Seller2	-7.381 (9.963)	0.395 (10.978)	5.227 (17.203)
Product2Seller3	-7.687 (9.949)	0.571 (10.960)	5.355 (17.148)
sellerprice	-0.012*** (0.001)	-0.008*** (0.002)	-0.015*** (0.002)
numberofsellers	-0.222*** (0.049)	-0.182*** (0.047)	-0.422*** (0.128)
stockoutratio	0.706 (1.707)	0.417 (1.726)	0.415 (3.225)
marketprice	0.009 (0.006)	0.010* (0.006)	0.022** (0.010)
λ :Product1		0.786*** (0.251)	
λ :Product2		0.296*** (0.108)	
λ :Seller1			1.016*** (0.301)
λ :Seller2			1.935*** (0.559)
λ :Seller3			3.712*** (1.142)

Table 5.4. MNL Model Results (cont.).

Observations	856	856	856
Log Likelihood	-977.695	-965.809	-963.481
AIC	1973.39	1953.617	1950.961
LR Test	213.726*** (df = 9)	237.499*** (df = 11)	242.154*** (df = 12)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01			

5.3. Nested MNL Models

After obtaining several insights regarding customer's buying decision under competition on an online market, one can wonder more about their decision mechanism. Do they make purchase instantaneously or the decision is finalized through some steps? Forming some clusters over alternatives and developing the model accordingly will help to answer these questions. Thus, the constructed MNL model to observe consumer choice behaviour is transformed through grouping alternatives which actually creates nests. It is wondered that what will happen if customers firstly decide on product or seller then make a comparison among clustered alternatives. Therefore, it is assumed that customer has two stage decision making process for purchase.

A statistically valid comparison can be made over the below described three models which are actually different in model structure, i.e., customer decision mechanism, whereas same according to the analyzed data. Log Likelihood and Akaike Information Criterion (AIC) are the parameters for this model comparison. These numbers are observed to have some idea regarding the model fitness. Since the aim is to maximize Log Likelihood, a higher value represents a better fit. On the other hand, a better fit model will have a smaller AIC value. Both rankings (through Log Likelihood and AIC) shows that nested models shows a better fit rather than the MNL model with a single decision mechanism (i.e., without any nest). Both nested models have smaller AIC as well as higher Log Likelihood values with a small difference between them (nested models).

Futhermore, since it will be observed that customers may shift between alternatives by different sellers for a product whereas they are more determined in their product selection, the MNL model with product nests is more valid for this kind of an online platform.

A nested MNL model separates set of alternatives into K nonoverlapping subsets and B_1 to B_K denotes nests. Then, utility that customer gains from alternative j in nest B_k is $U_j = V_j + \varepsilon_j$ where V_j as observed utility and ε_j is a random error whose value is not observed. It is assumed that unobserved utility vector is assumed to have a cumulative distribution given by $exp(-\sum_k(\sum_{j \in B_k} e^{-\varepsilon_j/\lambda_k})^{\lambda_k})$.

The parameter λ_k represents the degree of independence in unobserved utility among alternatives in nest k.

Thus, choice probability of alternative i in nest k is $P_i = \frac{e^{V_i/\lambda_k} (\sum_{j \in B_k} e^{V_j/\lambda_k})^{\lambda_k - 1}}{\sum_l (\sum_{j \in B_l} e^{V_j/\lambda_l})^{\lambda_l}}$.

Firstly, two nests are created over alternatives which divides them as Products 1 and 2 choices. It is illustrated as a tree diagram in Figure 5.1 (Product Nest). In other words, it is assumed that a customer initially decides on the product then makes a comparison among its sellers. Results are in Table 5.4 Column Product Nest.

Frequencies of alternatives remain the same which is normal since choices made (parallel with the number of sales in the data) are unchanged. Both sellers' prices and number of sellers are still statistically significant whereas coefficients are increased. It is expected due to the change of decision making process. When customer first decides on the product, then the seller, price and competition effects are slightly dropped and decrease the consumer choice probability less as much as 0.004 and 0.4, respectively (compared with MNL model results). This may show when the product decision is made firstly, customers are likely to have more utilities despite of increasing prices or more seller alternatives. Also, note that competition effect is still higher than the price.

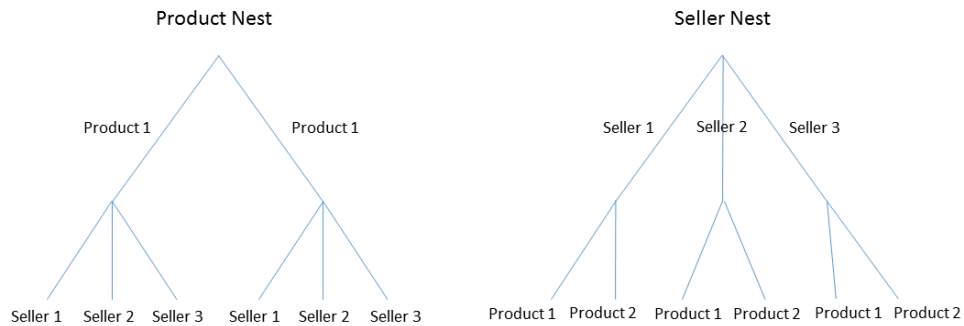


Figure 5.1. MNL Nest Structures.

Besides, an important output is the λ_k value which represents the independence of alternatives within nest k and one can observe correlation as $1 - \lambda_k$ value. Thus, in this model, higher value of λ within the nest of Product 1 means there is less correlation between the alternatives offered by the sellers of the product when it is compared to Product 2 nest. So, it may refer that customers may substitute between Product 2 alternatives presented by its sellers.

Similarly, another model is formed through dividing alternatives into three nests according to sellers. For instance, choices of buying Products 1 or 2 from Seller 1 is one nest and purchasing options by Sellers 2 and 3 describe the remaining in the same manner. Tree diagram of this structure is in Figure 5.1 (Seller Nest) and output can be seen in Table 5.4 Column Seller Nest.

Again, statistical significance of price and competition effects as well as constant utilities of buying Product 1 from Sellers 1 and 3 are still significant. However, unlike the product nested model, prices offered and number of sellers become more important for explaining choice. When prices go up and there are options by a higher number of sellers, customer choice probabilities decrease more when compared with the previous two models. Such increase in negative effects of price and competition on choice probabilities are 0.003 and 0.2 when compared to the model with single decision mechanism. When compared with product nested model, opposite impact of an increase in product price on the choice probability raises to 1.2 times of it and the negative effect caused by an additional seller is nearly doubled. It means when seller decision is made initially, then customers select the product, both price and competition seem more effective. Also, number of sellers is observed to have a higher effect on customers than products' prices in decreasing the utility.

Here, the estimated value of nest specific λ_k values (i.e., independence of products of a seller) should be analyzed. One can observe all three nests have log-sum coefficients greater than 1 which states there are more correlation among alternatives between nests rather than within a nest. In other words, consumer's choice is likely to be determined in product selection but he/she may substitute to another seller to buy the same product. Thus, it confirms that correlation over unobserved factors is much more among sellers rather than the products as stated previously. Such an outcome is thought to be related with dynamics of an online platform. In other words, online markets involve numerous sellers and so many alternatives and these results argue the shift of customers between that huge number of sellers.

Additionally, all of three models described above (MNL, product nested and seller nested models) have two common outcomes through obtained constant utility values of alternatives. These results argue the preference of Product 1 rather than its alternative and dominance of Seller 2 for that product. Firstly, in each model, constant utilities related with Product 1 which is Apple iPhone 8 64 GB are all statistically significant whereas such results could not be obtained for any alternative of Product 2,

i.e. Samsung Galaxy S8 64 GB. This points out a strong differentiation between two product choices and may be caused by some factors such as brand reputation, product features that are not included in model (such as user friendliness, design etc.).

A further analysis can be made for sellers of this product. Alternative of purchasing it from Seller 2 has positive coefficients in all these three models. This refers that there is an additional utility which is statistically significant that a customer will gain when buying Product 1 from Seller 2 compared to his/her competitors. In other words, when a buyer of Product 1 chooses Seller 2, he/she will have 0.569 more utility than making this purchase from Seller 1 (it is the base alternative and its constant utility is considered as zero) and over 1.3 more compared to Seller 3 according to the MNL model. This difference is slightly less for product nested model but when there are seller nests a much higher utility difference occurs in selecting Product 1 from Sellers 2 and 3.

5.4. Scenario Analysis

After obtaining Multinomial Logit models (with a single or multiple decision mechanism), several insights are gained. Regarding customers' thoughts before making a purchase decision, it is concluded that they seem to be more determined in their product decisions so they are more likely to decide on the product first then select the seller according to prices offered and number of other alternatives for that product (i.e., price and competition effects). On the other hand, through the analysis on the data observed shows the market shares among six alternatives (combinations of three sellers and two products). It is seen that Product 1 (Apple iPhone 8 64 GB) is more likely to be sold rather than its alternative (Samsung Galaxy S8 64 GB). Moreover, for both products Seller 2 (with id 2070783 on the platform) comes front in number of sales. Such an outcome is seen as the high constant utility values of alternatives including Product 1 and/or Seller 2 in model results (Table 5.4). This may be interpreted as the strong brand reputation of Apple and some features that are not observable in the model (counted in the constant utility value) like fast delivery, high ranking of Seller

2 as well as prices offered by the seller.

After obtaining the consumer choice models, analyzing them to describe the market dynamics, one can wonder whether or not these results may change? For example, the results are observed when the decision mechanism is changed (nested models) but what if prices change? Thus, market shares of alternatives are predicted through the MNL model with a single nest when all prices of six alternatives are increased by 10 percent. Moreover, for further comparison, market shares are also predicted when only Product 1 (Apple iPhone 8 64 GB) prices are increased by 10 percent. For both predictions, train set is determined as 40 days and the test data is last 6 days of the time horizon specified above while constructing models to understand the consumer behaviour. Predicted market shares of 6 alternatives (i.e., choice probabilities) over 46 days are given in Table 5.5.

These results show that when all products' prices are increased by 10 percent, a general shift towards Product 2 from Product 1 appears which can be understood by the decrease of choice probabilities of alternatives including Product 1 and the opposite for Product 2. This may support that customers are price sensitive that they may shift to the cheaper alternatives (in this case, Product 2 is the cheaper one) when prices are increased. In other words, when Apple iPhone 8 64 GB prices become much higher and the gap is also increased when compared to Samsung Galaxy S8 64 GB prices, they may change their product selection.

Moreover, predicted frequencies of alternatives when only Product 1 prices are increased by 10 percent also support this argument since it is clearly observed in such a case, alternatives including Product 2 is more likely to be purchased, i.e. even more compared to the first prediction (when all prices are increased). On the other hand, there is no obvious shift among sellers as a result of increased prices.

Table 5.5. Scenario Analysis over 46 Days.

Alternative	Observed		Predicted			
	(1)	(2)	(3)	(4)	(5)	(6)
Product1Seller1	0.2406	0.2419	0.1659	0.0094	0.1940	0.0462
Product1Seller2	0.5409	0.5402	0.3628	0.0206	0.4299	0.1005
Product1Seller3	0.0444	0.0445	0.0325	0.0022	0.0371	0.0105
Product2Seller1	0.0210	0.0178	0.0507	0.1125	0.0328	0.0694
Product2Seller2	0.1157	0.1180	0.2968	0.6373	0.2373	0.5677
Product2Seller3	0.0374	0.0382	0.0912	0.2182	0.0690	0.2057
Total	1.00	1.00	1.00	1.00	1.00	1.00
<p><i>Note:</i> (1) Observed results over model without any nest, (2) Observed results over model with Product Nests, (3) Prediction over model without any nest when increased prices, (4) Prediction over model without any nest when increased prices for Product 1 (5) Prediction over model with Product Nests when increased prices (6) Prediction over model with Product Nests when increased prices for Product 1 All increases in prices are 10 percent</p>						

Also, note that predictions are made through the MNL model with Product Nest for the same scenarios (when all prices and only Product 1 prices are increased 10 percent). It is the model which is obtained as the most suitable one for the online platform where sales transactions are observed. One can see that in terms of market shares, the decrease in Product 1 alternatives and so increase in its competitor (Product 2) happen again and more radical when only Product 1 prices are increased. However, these changes are observed less in number compared to the results obtained through MNL model without any nest. Thus, in other words, consumers may be more determined in their product selections despite of the increased prices when they first decide on the product before purchase.

6. CONCLUSION

Online sales data of smart phones by Apple, Samsung and Huawei is observed during a time period above one year. Parametric analysis is carried out through sales transactions of top products on the platform in its category. One needs to fix the bias caused by simultaneous causality between price and quantity, so 2SLS regression models are formed with instrumental variables. Also note that the double 11 campaign held on November, 11 has a dominant effect on sales quantity on the platform hence is put as control in each and every model constructed.

Fistly, sales transactions of Apple iPhone 8 64 GB are analyzed which has nearly 20 percent of total number of offers within the time period observed (376 days). A model is formed from the seller's point of view who sold the product mostly. It is seen that on a daily basis seller's price has a statistically significant negative impact on its sales amount whereas when the seller is given discount by the platform, its sales quantity is statistically expected to increase. Secondly, another model is formed to analyze Huawei P20 Lite 64 GB market which is in the second place in terms of total revenue just after Apple iPhone 8 64 GB. Model result argues that daily average price of the product and ratio of sellers who are left without any stock on a day affect the daily total quantity in reverse direction. Lastly, online daily sales data of Apple iPhone 8 Plus 64 GB which takes second place after Huawei P20 Lite 64 GB in terms of sales amount is analyzed. Two models are formed - second one includes the stock-out sellers' ratio - and as a result, again daily average price of the product and the ratio of stock-out sellers have statistically negative effect on its total sales quantity on a day.

Before constructing such models, for each one, initially instrument candidates are determined which are thought to be strong. This decision is made through observing the correlation matrices including the outcome (quantity), endogenous variable (price) and instrument candidates. Then, a validity check is made for each candidate through diagnostics tests to form a model. A strong instrumental variable is needed to be

correlated with the price and independent of the error term.

Another significant outcome is fixing the simultaneous bias due to relationship between the price and quantity as well as the selection bias which can be caused by observing only sales data. Since zero sales are also observable in this analysis unlike many researches, sharp price elasticities are obtained. It is seen that these bias significantly change the model results. Price elasticities and/or ratio of stock-out sellers as well as the ones given discount by the platform change in either direction (decrease or increase impacts on sales amount). Apple iPhone 8 64 GB market model concludes even a sign change in price elasticity. Price seems to have a positive effect on quantity - which is not logical - when IVs are not included in the model.

Moreover, after using such models to describe the market dynamics, predictions are made through the market models. The data observed for constructing each model is divided into two sets as train and test where the test data is chosen as the last 30 days of product's sales period. Both in-sample and out-of-sample prediction results are compared with actual results. Evaluations are made through accuracy measures and results for in-sample and out-of-sample predictions are compared with each other as well as checked with same measures for ten sample data of 30 days.

It is seen that in-sample predictions (over the complete train set) have significantly small errors which signals a strong accuracy. However, it is obtained that this is due to being overfitting. Also, predictions for testing -over sample data sets (same length with the test data, obtained from the train set)- are found to have similar results with the out-of-sample prediction for each 2SLS regression market model.

On the other hand, consumer choice models are formed with the MNL approach. Apple iPhone 8 64 GB as the leader with over 18 percent of the total sales transactions within the time period observed and its main competitor Samsung Galaxy S8 64 GB are selected for investigation. Top three sellers of each of these two products are determined so six product-seller alternatives are formed. MNL model is formed over

46 days where all of these six alternatives are present on the platform. It is aimed to understand consumer behaviour (decision mechanism) before making purchase.

To have a better understanding, also nests are created for products as well as sellers and nested MNL models are formed. All of three models (MNL models without any nest, with product nests and seller nests) concludes that people are more determined in their product choices. Thus, one can model the buying decision mechanism as firstly choosing the product and then deciding on the seller which is actually the MNL model with product nests. This outcome is thought to be logical for the real life buying behaviour for smart phones on an online platform. A person who wants to buy a smartphone is seen as more determined in brand and model (product) selection and then makes a decision among its sellers.

Additionally, scenario analysis are made with increasing prices (for all products and a single product separately). This aims to see how customers may react to changing prices with their buying decisions. Results agree with the negative effect of increasing prices where people change their mind to buying the cheaper alternative. However, it is also observed that they may be affected by some alternative specific conditions. These can be brand reputation, seller's rating and/or service quality. Also, results support that they are more determined in their product selection rather than the seller.

These results can be used by the platform. 2SLS regression models may help to describe how price and competition affect on sales quantity on the platform. Moreover, the platform may get benefit from these models to predict daily sales amount for specific sellers as well as product groups (models, brands etc.). Thus, the platform may see what will happen with changing prices and stock levels and make some decisions -like offering platform discount- accordingly. On the other hand, consumer choice models may be a guide to the platform to understand how customers make purchase.

Beyond this research, further improvements and changes can be considered. One can make non-parametric analysis without choosing representative products and ob-

serve their market independently. Also, another product category rather than smart phones may give different outcomes. Instrumental variables can be used in MNL models as well for sharper results. In the sales data observed, original product prices are in different currency whereas converted numbers in Turkish Liras are used. When prices in original currencies are used the researcher can get rid of unobservable effects of changing currency exchange rates on model results.

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APPENDIX A: OLS REGRESSION RESULTS WITH INSTRUMENTAL VARIABLE CANDIDATES FOR THREE PRODUCTS

OLS regression results are given in consecutive three tables for top seller model of Apple iPhone 8 and market models of Huawei P20 Lite market and Apple iPhone 8 Plus. for each model, instrumental variables are included in models individually with controls where outcome is daily price of each product.

Table A.1. Apple iPhone 8 Top Seller OLS Regression Results for IV Selection.

	<i>Dependent variable: sellerprice</i>		
dwmeanp	3.263*** (0.129)		
numberofcompetitors	−19.998*** (0.684)		
usd	406.298*** (53.624)		
sellerplfdiscount	−370.987*** (32.168)	−129.579*** (28.582)	−250.491*** (48.778)
d11	−398.465* (208.693)	21.326 (189.870)	−289.922 (320.385)
Constant	−1,486.577*** (256.343)	5,737.566*** (37.677)	2,706.786*** (300.126)
Observations	376	376	376
Adjusted R ²	0.643	0.706	0.159
Residual Std. Error (df = 372)	206.622	187.609	317.170
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01			

Table A.2. Huawei P20 Market OLS Regression Results for IV Selection.

	<i>Dependent variable: marketprice</i>
plfdiscouts	−1,309.202*** (161.492)
stockouts	−1,042.772*** (66.564)
d11	−2.210 (203.115)
Constant	2,979.401*** (41.802)
Observations	376
Adjusted R ²	0.395
Residual Std. Error	200.987 (df = 372)
<i>Note:</i> *p<0.1; **p<0.05; ***p<0.01	

Table A.3. Apple iPhone 8 Plus Market OLS Regression Results for IV Selection.

	<i>Dependent variable: marketprice</i>
plfdiscoun	-1,524.077*** (187.546)
stockouts	-474.176*** (111.220)
d11	-233.110 (188.870)
Constant	6,562.946*** (55.531)
Observations	376
Adjusted R ²	0.146
Residual Std. Error	187.906 (df = 372)
<i>Note: *p<0.1; **p<0.05; ***p<0.01</i>	

**APPENDIX B: DIAGNOSTIC TEST RESULTS OF 2SLS
REGRESSION MODELS WITH EACH INSTRUMENTAL
VARIABLE CANDIDATES FOR APPLE IPHONE 8**

The diagnostic test results are listed for models formed with each instrumental variable candidate individually for Apple iPhone 8 top seller model described in Chapter 4. IV candidates are average price if dishwashing machines on the platform, number of other sellers of the product and USD to TL exchange rate.

Table B.1. Apple iPhone 8 Diagnostic Test Results for IV Selection.

	statistic			p-value		
	(1)	(2)	(3)	(1)	(2)	(3)
Weak instruments	615.77	<2e-16***	846.34	<2e-16***	62.72	2.79e-14***
Durbin-Wu-Hausman	4.96	0.027**	3.75	0.054*	0	0.95

Note: *p<0.1; **p<0.05; ***p<0.01, *df*: (1,372) for Weak instruments and (1,371) for Durbin-Wu-Hausman, *dw*meanprice (1), *numberofcompetitors* (2) and *usd* (3) as individual IVs, respectively

APPENDIX C: 2SLS REGRESSION RESULTS WITH CPI ADJUSTED PRICES FOR HUAWEI P20 LITE

The below table shows 2SLS regression results over Huawei P20 Lite Market model with Consumer Price Index (CPI) adjusted prices. Same model in Chapter 4 constructed for Huawei P20 Lite is used with prices in the data observed divided by CPI values on those days.

Table C.1. Huawei P20 Lite Market Model Results CPI Adjusted.

	<i>Dependent variable: totalquantity</i>
log(marketprice)	−96.09*** (20.99)
stockouts	−97.52*** (10.09)
d11	1884.17*** (17.00)
Constant	230.22*** (40.75)
IV	plfdiscounts
Observations	376
Adjusted R ²	0.971
Residual Std. Error	16.840 (df = 372)
Weak instruments	82.559***
Durbin-Wu-Hausman	7.805**
<i>Note: *p<0.1; **p<0.05; ***p<0.01</i>	