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BREAKING DOWN ONLINE PRICE DISPERSION

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Abstract:

Price dispersion is defined as a situation where identical, or similar, products are sold by sellers at different prices. In a world without any price dispersion, we would expect homogeneous prices across all sellers especially online since there are essentially no search costs involved. However, that is not what is observed in real life, where products with identical characteristics are sold at varying prices. This paper attempts to break down the cause of this dispersion by analyzing what leads to online price dispersion, how the price of the product is affected by product characteristics, the seller characteristics, market variables etc.

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Introduction to Price Dispersion:

In a world with perfect competition, one would expect to observe the "law of one price", which states that similar goods should sell at uniform prices, creating perfect competition. This is because online platforms provide low barriers to entry, easy access to information as well as low transaction costs (Lindsey, 2006). Online marketplaces are what Adam Smith would describe as perfect competition, which should result in high price competition and weak market power (Lindsey, 2006). Essentially, at least in theory, similar products should be selling for the same price and there should be reduced profit margins for sellers. However, it is often seen that this law of one price fails to hold in the real-world markets, especially online. It is often observed that in a given market, different sellers sell similar products at different prices. This phenomenon is known as price dispersion (Zhuang, 2018). Generally, it is believed that one of the reasons for price dispersion is due to the fact that consumers do not have perfect knowledge about the prices being charged by different sellers, since researching different prices in a market involves a search cost (Zhuang, 2018). Therefore, when one shops online, we expect to see uniform prices since prices and product information are more readily accessible and search costs are negligible (Baye, 2001). However, contrary to expectations, it is observed that price dispersion is prevalent online, even for products that appear to be homogenous (Baye, 2001). This paper aims to examine why prices vary for tablets being sold on the Chinese platform Tmall, how much of the difference in prices can be attributed to product characteristics, seller characteristics, time period etc and if there is a hidden search cost. We expect to find that even though most of the variation in price can be explained due to various factors, there is still a significant part that cannot be observed. We believe this is the search cost associated with shopping online.

Literature review:

Ever since the inception of online retail, there have been various studies that have addressed the issue. This is hardly surprising since the phenomenon of price dispersion online defies what is expected. Different researchers have addressed varying issues and have contributed to the enigma that is online price dispersion. For example, a paper compared prices over a period of eight months for one thousand best-selling consumer electronic products (Baye, 2001). They found that when the number of firms increased, the dispersion was as small as 3.5% whereas when the number of sellers decreased, the dispersion was as high as 22% (Baye, 2001). At a general level, one may conclude that prices online start converging as the number of sellers increases and consumers have better knowledge. This has been shown to be consistent with the convergence hypothesis, which state that price dispersion is transitory and will disappear as markets mature (Fan, 2006).

A parallel can be drawn between how prices in developed countries have converged, as compared to emerging countries who haven't developed yet and the convergence of prices online. For example, in a study by Fan, the convergence to the law of one price in the transitional economy of China. It was found that the pattern as well as the speed of convergence is highly comparable to those of in developed economies, like the United States of America (Fan, 2006).

This relates directly to the topic of the thesis since it is shown in later sections that when the number of sellers increased in the market, there was a decrease in the level of price dispersion (Table 8). It is shown that during a certain month, there was an increase in the number of sellers in the market. As a result, the degree to which the price of the product could be explained by product characteristics, seller characteristics and market variables increased, hence decreasing the level of price dispersion in the market.

Since there is no doubt about the existence of price dispersion, economists have now proceeded to find out why it occurs. Empirical studies have studied the relationship between average prices and the level of dispersion (Lindsey, 2018). Contrary to expectations, the study concluded that when the mean price of durables increased, the level of price dispersion increased as well (Lindsey, 2018). The author is of the opinion that this occurs due to the aggregation of individual level price perceptions. For example, it was found that consumers buying durables were more inclined to not search prices when buying durables since savings are viewed in relative terms i.e. "a $50 saving on a $100 item is viewed differently than a $50 saving on a $500 product" (Lindsey, 2018).

Some other work done on the topic includes studying the morphology of prices i.e. studying the shape and structure of distribution of price at which identical goods are sold in a given market, during a given time period (Kaplan, 2015). Although this study was done using data from physical stores, this has general applicability for anyone studying the convergence towards the law of one price and price dispersion. After inspecting the shape of price dispersion, using decomposition, three prominent reasons for observed price dispersion were examined. These were broken down into – i) a store component which is defined as the average price of all goods where the transaction took place, ii) a store specific good component, defined as the average price of a particular good at that store, compared to the average price of all goods in that store and iii) a transaction component which has been defined as the price of the good in a particular transaction as compared to the average price of that particular good in the given particular store (Kaplan, 2015). The findings of this particular study are interesting because it was concluded that price dispersion does not occur chiefly due to one store being more expensive than the other. However, it occurs because the average price of a specific good varies substantially, and even at a given store, the price of a specific good varies across transactions. This gives us a reflection about how prices can be different not only because of different sellers but also because of the size of a transaction and the store.

A similar, but simpler, study was also done to examine price dispersion in the context of online malls (Petrescu, 2011). She studied the differences and similarities between physical stores and the marketplaces found online and then proceeded to discern which online aspects are important to consumers when making purchases online (Petrescu, 2011). This study is different from other studies about online price dispersion since most of them use shopping bots to gather data, Petrescu however, used data directly from Amazon which makes it more relevant to today's customer behavior as well as the dataset I will personally be working with. It also took into account factors distinctive to the internet, like shipping charges, seller ratings and consumer reviews. Since the dataset that I used also employs seller characteristics in the form of rating provided by consumers, this study helps draw a parallel, as well as help confirm results, between what I observed and what was observed by Petrescu.

It was hypothesized, and proven true, that lowest price does not mean the highest number of sales as other factors also influence the buyer's behavior. She found that contrary to expectations, the internet did not give rise to Bertrand price competition (Petrescu, 2011).

Bertrand price competition refers to the phenomenon where in a market with a given number of sellers, sellers choose their price independently and simultaneously in order to gain the maximum profits possible (Quickonomics, 2018). The demand at this price then determines the quantity supplied (Quickonomics, 2018). Each seller, hence, tries to undercut prices to gain market power (Pettinger, 2017). This continues until the price is equal to the marginal cost (Pettinger, 2017) and hence, an efficient equilibrium is reached where sellers are not earning economic profits, presuming all active sellers have the identical marginal costs.

Instead, it was found that the there is a positive relationship between the shipping costs and price of product, which in turn affects price differentiation. There was also found to be a positive relationship between the number of sellers and dispersion in price. Factors like consumer reviews and seller ratings too affected the choices made by consumers as well as the disparities in prices (Petrescu, 2011). Essentially, the key conclusion of the study was that imperfect information and search costs are not the sole reasons for price dispersion across an internet marketplace (Petrescu, 2011). This study is relevant because after proving that search costs exist, the thesis will try to discuss what other factors might be in play that result in varying prices. Besides that, the results observed by Petrescu are similar to what was observed in this study, hence making it a valid benchmark.

Another interesting aspect of price dispersion was noted by Ancarani as well as Pan (Pan, 2009). They both conjectured the impact of multi-channel retailers on price dispersion. Ancarani found that while e-tailers, or online retailers, post lower prices than traditional or multi-channel retailers, when shipping costs are included, e-tailers actually have higher prices (Ancarani, 2008). They also found that while prices from different e-tailers, including traditional and multi-channel, had low standard deviation, when shipping costs were included, the dispersion increased significantly, especially for multi-channel sellers (Ancarani, 2008). They were hence able to conclude that sellers use this as a way to differentiate themselves and to keep costs and dispersion high (Ancarani, 2008). Pan (Pan, 2001) had similar conclusion and stated that as a result of more efficient delivery and return services and greater consumer trust, multi-channel retailers had higher equilibrium price (Pan, 2001). It was also established that these prices are higher because they provide better pick-up and return services and in general have a higher level of trust among buyers (Pan, 2001). However, this conclusion varied, depending on the measure of price, e.g. with or without shipping charges, and hence gives rise to opportunities for product differentiation (Pan, 2001).

A somewhat similar result was observed while breaking down the price of a product. I found that the service score and description score of the seller had a direct relationship with the price of the product. Also, the shipping factor had a negative coefficient, and hence an inverse relationship with the total price. This means that as shipping gets cheaper, the total price decreases. These observations resonate with the observations of Pan and Ancarani who concluded that diverse shipping methods, service etc help sellers differentiate themselves and hence, lead to different prices.

The last study used as a reference was done with an objective to find the key drivers for varying prices online (Pan, 2009). This study, in a way, builds from the study done by Petrescu by giving us more comprehensible results by introducing parameters that characterize online services. This study has also followed an approach similar to this paper's and hence, provides a general idea for the structure of the paper's organization and expectations. According to the study, there are five underlying factors that characterize an online service, namely shopping convenience, product information, shipping and handling, pricing policy and reliability. They also considered other characteristics like trust, consumer awareness and time of entering the online market. The premise of the study is based on the fact that none of the existing propositions, ranging from high search costs and imperfect information to the size of market and number of competitors, have been successfully able to justify why such dispersions arise. Pan focused on identical products and collected data about the different prices from varying sellers. They then proceeded to collect data about seller characteristics, the “trust” placed in different sellers as well as the traffic on each website. After collecting the data, it was analyzed by separating it into different “clusters” as well as by running price dispersion regressions. It was found that market characteristics are predominantly responsible for the variation in prices. They also concluded that sellers affect prices through shipping and handling, through the trust placed in them by consumers as well as through shopping convenience. It was also found that sellers who charged higher prices were generally sellers who had entered the market earlier, provided more flexible and economically feasible shipping options and who had higher prices overall, and not necessarily those who provided superior services.

This study is relevant since it agrees directly with what was observed in my regressions-product characteristics are predominantly responsible for varying prices and eventually other factors help buyers make decisions. Besides that, our results also concluded that sellers can influence some part of the price through shipping, descriptions and services, just like Pan concluded.

Introduction to Dataset and Variables:

The data set I have consisted of products sold on a Chinese platform online during a period of seven months, October 2014 till April 2015, in four different locations. The online platform, “Tmall”, is an online marketplace created specifically for Chinese consumers and is operated by Alibaba (Pilon, 2017). The dataset was chosen because unlike websites like Amazon and eBay where anyone can sign up as a seller, this website hosts only trusted brands and sellers can set up their own “stores” to engage in the market (Pilon, 2017). Hence, this data was chosen to provide the most accurate representation of how an online marketplace reacts with minimal risks involved. While the website hosts numerous sellers selling various products, ranging from personal care and skin care to apparel and electronics (Pilon, 2017), my data set was restricted to electronic tablets of varying specifications.

The tablets were identified and differentiated on the basis of the seller characteristics, the product characteristics and the time of the year. The variables are described in Table 1.

Table 1. Description of Variables

Variable Name	Description
Month	Month of year
Screen	Screen size of tablet
Tot_price	Total price
Storage	Storage available on the tablet
RAM	RAM of the tablet
OS_1	Operating Software- Android
OS_2	Operating software- Apple
OS_3	Operating software- Unknown
Mktage	How long the product has been on the market
Loc_1	Location of seller
Loc_2	Location of seller
Loc_3	Location of seller
Loc_4	Location of seller
Des_score	Seller rating- How well the product was described
Sev_score	Seller rating- How good was the service during and after sale
Shp_score	Seller rating- How fast/cheap was the shipping
Brand	Brand of the tablet
Num_sellers	Number of sellers selling a tablet with same specifications
Pro_char	Number of products in the market with the same specifications

Table 1. Description of variables

Limitations to Dataset:

The dataset uses list prices shown online by the sellers. It does not take into account any coupons or gift-cards that may have been applied by the consumer themselves. Another major limitation are the seller ratings. Since these are provided by consumers after they receive their product and are provided voluntarily, there is a chance of bias. Buyers who are extremely pleased or extremely dissatisfied with their product are more likely to rate the product, rather than consumers whose product was in line with their expectation (Lafky, 2014). This may be done either to help other buyers make more informed decisions and/or to punish, or reward, the seller (Lafky, 2014). Products of moderate quality however, would not evoke such behaviors (Lafky, 2014).

Hence, the three seller ratings, description score, service score and shipping score, may not be a true reflection of the seller themselves.

Introduction to Regressions:

While the previous version of the excerpt introduced the topic of price dispersion, why it occurs even when one would not expect it to and the factors that affected it, we will now discuss the regression model for the thesis and how it can help us determine how price of a product is affected by different factors.

Regression models:

I will begin by using a simple regression model that explains price as a function of seller characteristics, product characteristics, market variables and an error term. The aim is to keep the methodology uncomplicated and direct hence, it was decided to take a simple equation that would be easy to comprehend and work with. Hence, the equation looks like the following:

$$Price_{s,j,t} = \beta_i * Productcharacteristics_{j,t,w} + \alpha_i * Sellercharacteristics_{s,t,k} + \gamma_i * MarketVariables_{j,t} + \varepsilon_{s,j,t}$$

In a situation with no price dispersion and an almost perfect competition, we would expect that the price is explained entirely by the seller characteristics and the product characteristics. Here, we would expect the constant, or the error term, to be zero. However, as has been established earlier, that is not always the case and hidden costs, in the form of search costs etc, exists hence making the error term not equal to zero.

The methodology is to run hedonic regressions using Stata to determine what kind of affect different factors have on the price.

Hedonic pricing model is defined as a "revealed preference" method that is used to estimate the extent to which each factor affects the price of a product (Chen, 2018). Hedonic regression models regress the price of one unit of a product on a function of characteristics, including a time variable (Kenton, 2019).

This method has been used extensively by Pan who, in his paper, combined two theories of price dispersion- dispersion due to search costs and dispersion due to other explanations, to determine how e-tailor, defined as an online retailer, quality affects prices (Pan, 2002). Although it was found that reliability has a significant impact on price and hence, e-tailer quality can explain price dispersion only to a certain extent (Pan, 2002), the model itself was rather straightforward, equating price of a product to a sum of its attributes, the unmeasured service attributes and changes due to pricing policy etc (Pan,2002) and serves as an inspiration for my model.

I will begin by regressing price on product characteristics and see how it is affected. Eventually, I will keep adding more factors, like seller characteristics, market variables and if possible, try to explore market characteristics further by determining how product characteristics determine the other's effect on price etc.

Product characteristics:

We first began with trying to see how product characteristics affect price. Product characteristics were chosen first since it was presumed that a rational consumer would put more emphasis on the specifications of the type of tablet available before taking into account other factors, like seller characteristics etc (Pan, 2009). To do that total price was regressed on varying product characteristics and varying attributes were added to the regression at each step. It was found that as more characteristics are added to the variable, some help explain variations in price more than others.

To begin with, the price of the product was regressed on the amount of storage available on the tablet. It was found that 67.04% of the price is explained just storage by itself. The coefficient, by itself, had a value of 31.52 and passed the P-test to be significant enough to not be ignored (Table 2).

Table 2. Price regressed on Storage

					R-squared	0.6704
tot_price	Coef.	Std. Err.	T	P>|t|	[95% Conf. Interval]	
storage	31.51687	0.150085	209.99	0	31.2227	31.81105
_cons	1049.049	8.477044	123.75	0	1032.434	1065.665

Table 2. Price regressed on Storage

The RAM of a product affects not only how fast the device is, but also the overall performance ("Why is RAM so important"), hence it was no surprise to see that it was significant enough, with a coefficient of 45.54823, to increase the R-squared from about 67% to over 67.6%. As expected, when the screen size was taken into consideration, with a significant coefficient of 300.19, the R-squared increased to over 72% (Table 3).

Table 3. Price regressed on storage, RAM and screen

					R-squared	0.7210
tot_price	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
storage	26.36682	0.162214	162.54	0	26.04887	26.68477
ram	37.75455	2.169567	17.4	0	33.50204	42.00706
screen	300.1908	5.081197	59.08	0	290.2313	310.1503
_cons	-1462.64	42.37527	-34.52	0	-1545.703	-1379.59

Table 3. Price regressed on storage, RAM and screen

As more factors were added, like os_1 os_2 and os_3, corresponding to different types of operating softwares the R-squared increased from 72.10% to 72.33%, 72.84% and lastly, to just below 73% (Table 4).

Table 4. Price regressed on storage, RAM, screen and different operating software

tot_price	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
					R-squared	0.7296
storage	27.83543	0.173905	160.06	0	27.49456	28.1763
ram	23.078	2.292389	10.07	0	18.58474	27.57125
screen	323.1873	5.119882	63.12	0	313.1519	333.2226
os_1	-67.944	41.83317	-1.62	0.104	-149.9401	14.05208
os_2	1206.559	88.00791	13.71	0	1034.057	1379.061
os_3	-421.109	41.8936	-10.05	0	-503.2237	-338.995
_cons	-1536.9	57.36156	-26.79	0	-1649.328	-1424.46

Table 4. Price regressed on storage, RAM, screen size and different OS.

When the market age, defined as how long the product has been selling for, of the product was taken into account the R-squared increased to almost 73.1%. Interestingly though, when os_3 was added to the regression, os_1 had a P-value so high that it did not pass the significance test. Hence, this signifies that the regression may not truly reflect the changes in price since os_1 isn’t significant enough. However, when the regression was set up without os_3 but with other product characteristics, including the market age, there was close to no difference in the R-squared but os_1 was significant again.

Another interesting aspect of regressing price on product characteristics were the coefficients of the product characteristics at various levels of regression. Although they were positive, the intensity changed with respect to other characteristics being added etc. For example, the coefficient pertaining to storage went from 31.51 to 26.366 when elements like RAM and screen were added but increased to almost 28.00 when various operating softwares were added to the equations. As a result, it is safe to conclude that the weight on one certain characteristic varies, depending on what other aspects of the product are being considered.

Interestingly, it was also observed that when os_3 was added, not only did os_1 become insignificant, but also had a negative coefficient, which means that as the price of the product increases, os_1 has lesser influence on it. Similar results were observed for operating software os_3 as well. When added to the regression, it was observed that, despite the increase in R-squared, the characteristic had a coefficient of -421.1092. Hence, it can be interpreted that an increase in os_3 by one would cause a decrease in the price of the product by $421.1092 ("DSS-Interpreting Regression Output"). Lastly, what stood out was the fact that os_2 always had the highest coefficient, no matter how the regression was set up. This can help us conclude that when accounting solely for product characteristics, the operating software pertaining to os_2 had the most influence on the price of the product.

Seller characteristics:

I moved on to regressing the price of the product on just seller characteristics. Some of the seller characteristics, like the shipping score, description score and service score are based on the average of past consumer ratings. Since these ratings are voluntary the likelihood of biases exists. However, since it is not possible to discern these biases, they have been ignored. It is notable to mention that these three ratings- the shipping score, the description score and the service score are correlated to each other by 0.9896, 0.9914 and 0.9949 respectively (Table 5).

Table 5. Correlation between the three seller scores

	sev_score	des_score	shp_score
sev_score	1		
des_score	0.9949	1	
shp_score	0.9914	0.9896	1

Table 5. Correlation between the three seller scores

I began by regressing the total price of the product on sellers located in loc_1, defined as the first location, and then proceeded to add the second, third and fourth location to the regression. It was observed that not only did the seller's location have but a small effect on the R-squared, but also that at most points, some of them were also insignificant. For example, the R-squared rose from 0.05% with just location one to 0.05% and eventually to almost 0.5% with all four locations (Table 6). This negligible change in the R-squared alludes to the fact that because these sellers are selling on an online platform, their location does not affect the prices.

Table 6. Price regressed on different locations of sellers

					R-squared	0.0049
tot_price	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
loc_1	18.86717	33.42316	0.56	0.572	-46.64468	84.37903
loc_2	-283.775	42.66552	-6.65	0	-367.4024	-200.147
loc_3	240.6129	55.41769	4.34	0	131.9901	349.2356
loc_4	57.85426	69.72766	0.83	0.407	-78.81708	194.5256
_cons	1969.849	28.53525	69.03	0	1913.918	2025.78

Table 6. Price regressed on different locations of sellers

This result is confirmed by a study done by Arup and Sandeep (2001), where they looked at the competitiveness of sellers online and how they differentiate themselves from each other. They concluded that as long as delivery costs are not too sensitive, location was not a prominent factor when determining prices (Arup, 2001). They were also of the opinion that the internet has, in fact, reduced the location specific power sellers had and hence, has increased the intensity of competition (Arup, 2001).

What stood out was that when other locations were added to the regression, the P-value for the first location was high enough that the null hypothesis could not be rejected and hence, the characteristic was deemed to be statistically insignificant. Similar results were observed for the fourth location as well.

Eventually, more significant characteristics- seller scores etc were added to the regression. As expected, the shipping score, description score and service scores had a relatively higher impact on the R-squared than the location of the seller. Collectively, the three characteristics raised the R-squared from 0.49% to almost 1.00% (Table 7).

Table 7. Price regressed on seller locations and descriptive scores.

					R-squared	0.0089
tot_price	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
loc_1	-26.427	33.72489	-0.78	0.433	-92.53029	39.67623
loc_2	-297.483	42.62144	-6.98	0	-381.0241	-213.942
loc_3	248.3495	55.41582	4.48	0	139.7304	356.9686
loc_4	33.90804	69.73608	0.49	0.627	-102.7798	170.5959
shp_score	-1661.6	206.7052	-8.04	0	-2066.756	-1256.44
des_score	597.733	265.2697	2.25	0.024	77.78479	1117.681
sev_score	1179.115	293.6918	4.01	0	603.4571	1754.772
_cons	1437.533	123.9817	11.59	0	1194.52	1680.546

Table 7. Price regressed on seller locations and descriptive scores

Interestingly though, even though all these characteristics were significant enough to not be rejected, the coefficient for the shipping score was negative. A negative coefficient means that when the coefficient for shipping score is increased by one, the total price is expected to decrease by as much as the coefficient ("DSS- Interpreting Regression Output"). This result is consistent with expectations since a higher shipping score might mean that the seller used cheaper shipping methods, hence lowering costs for the consumer. Since other features do not directly contribute to the upfront cost of the product, their positive coefficient is not as thought provoking. The only time R-squared was higher than 1.00% was when the month characteristic was added (Table 8). However, we will discuss that later in the market variable section.

Table 8. Price regressed on seller characteristics and month

					R-squared	0.0114
tot_price	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
loc_1	772.754	112.8589	6.85	0	551.5421	993.9658
loc_2	-297.309	42.56841	-6.98	0	-380.7466	-213.872
loc_3	249.6242	55.34712	4.51	0	141.1398	358.1087
loc_4	39.02146	69.65271	0.56	0.575	-97.50296	175.5459
shp_score	-1529.18	207.218	-7.38	0	-1935.347	-1123.02
des_score	661.3253	265.0782	2.49	0.013	141.7526	1180.898
sev_score	971.7778	294.6545	3.3	0.001	394.2334	1549.322
month	92.99167	12.53362	7.42	0	68.42485	117.5585
_cons	460.9172	180.7202	2.55	0.011	106.6923	815.1421

Table 8. Price regressed on seller characteristics and month

Market variables:

A rather interesting point of view can be to see how the number of sellers in the market is affected by the market variables, how demand changes over a given period of time, and product characteristics and the effect on price because of that. I created a new variable called "num_sellers" to signify the number of sellers in the market. It is defined by the number of sellers in the market during a certain month in the first step, number of sellers during a certain month selling a certain storage type in the second step and so on.

Intuitively, we'd expect to see two effects in play- the competition effect and the demand effect. Since in a competitive market there are many firms with no market power, the firms are deemed as price takers and not price makers. Hence, the number of sellers should not have a very big impact on how the product is priced.

This expectation was proved true when doing the coefficient analysis for the market variables. The new variable- num_sell was first created by summing up all the sellers selling a product with the same storage, which gave a resultant coefficient of 0.0181 (Table 9). The positive coefficient implies that there was enough demand. So much so that the effect of competition was not strong enough to drive sellers out for a product of a certain specification.

Table 9. Number of sellers for tablets of same storage

					R-squared	0.7354
tot_price	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
storage	28.05154	0.17697	158.51	0	27.70466	28.39841
ram	24.07175	2.272152	10.59	0	19.61816	28.52533
screen	318.2503	5.124068	62.11	0	308.2067	328.2938
os_1	-67.4192	41.64171	-1.62	0.105	-149.04	14.20162
os_2	1176.296	87.39881	13.46	0	1004.988	1347.604
os_3	-327.653	42.72678	-7.67	0	-411.4002	-243.905
mktage	65.97356	11.65246	5.66	0	43.13389	88.81323
loc_1	-81.5768	19.79848	-4.12	0	-120.3832	-42.7703
loc_2	-282.2	22.10981	-12.76	0	-325.537	-238.863
loc_3	149.0749	28.65228	5.2	0	92.9143	205.2354
loc_4	23.22126	36.09039	0.64	0.52	-47.51856	93.96108
shp_score	-647.294	107.073	-6.05	0	-857.1646	-437.423
des_score	668.4707	137.3779	4.87	0	399.1999	937.7415
sev_score	21.13362	151.9443	0.14	0.889	-276.6884	318.9556
num_sellers	0.018165	0.002284	7.95	0	0.0136869	0.022642
_cons	-1835.59	86.42258	-21.24	0	-2004.989	-1666.2

Table 9. Number of sellers for tablets of same storage

It was also observed that the service score failed to be statistically significant at this step. Hence, it can be said that when accounting for the sellers selling tablets of the same storage, the service score does not affect the price of the product. Similar conclusions can also be drawn about the first operating software as well as the fourth location of where sellers were located.

As more characteristics were added, like RAM, screen size and different types of operating softwares, the coefficient became more positive, going as high as 0.028, but remained extremely close to zero. It was significant to note that when the brand factor was taken into consideration, not only did the R-squared increase from 73.47% to over 74%, but the coefficient of the variable for the number of sellers also increased to almost 1 (Table 10).

Table 10. Number of sellers for a certain type of storage, RAM, screen size, OS and brand

					R-squared	0.7409
tot_price	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
storage	27.28461	0.171701	158.91	0	26.94806	27.62115
ram	24.48456	2.247836	10.89	0	20.07864	28.89049
screen	339.6764	5.065302	67.06	0	329.748	349.6048
os_1	-98.5775	41.22161	-2.39	0.017	-179.3749	-17.7801
os_2	1268.675	86.58316	14.65	0	1098.966	1438.384
os_3	-334.711	41.71567	-8.02	0	-416.4763	-252.945
mktage	63.14006	11.53185	5.48	0	40.53679	85.74333
loc_1	-63.9151	19.60971	-3.26	0.001	-102.3516	-25.4786
loc_2	-224.435	22.04554	-10.18	0	-267.646	-181.224
loc_3	154.6542	28.35467	5.45	0	99.07691	210.2314
loc_4	11.93345	35.71405	0.33	0.738	-58.06871	81.93561
shp_score	-642.048	105.9555	-6.06	0	-849.7287	-434.368
des_score	494.5795	136.1781	3.63	0	227.6604	761.4986
sev_score	178.6574	150.5418	1.19	0.235	-116.4156	473.7305
num_sellers	0.799034	0.034973	22.85	0	0.7304847	0.867584
_cons	-1946.95	85.34459	-22.81	0	-2114.232	-1779.67

Table 10. Number of sellers for a certain type of storage, RAM, screen size OS and brand

The only other anomaly from this was when the “month” characteristic was added to the equation. It was observed that the coefficient reached its highest value at 4.607. However, there was also a slight decrease in the R-squared (Table 11). A possible reason for this observation may be that during a certain month the demand was high enough to make it lucrative for sellers to not only enter, or exit, the market, but also be able to able to affect the price more than before (Li, 2013).

Table 11. Number of sellers for a certain type of storage, RAM, screen size OS, brand and month

					R-squared	0.7397
tot_price	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	

storage	27.37295	0.171872	159.26	0	27.03607	27.70983
ram	24.48324	2.25314	10.87	0	20.06692	28.89956
screen	335.2472	5.060163	66.25	0	325.3289	345.1654
os_1	-102.672	41.33907	-2.48	0.013	-183.6993	-21.6441
os_2	1240.567	86.74607	14.3	0	1070.538	1410.596
os_3	-352.123	41.78448	-8.43	0	-434.0238	-270.223
mktage	65.44609	11.55803	5.66	0	42.79151	88.10068
loc_1	-47.8295	19.71742	-2.43	0.015	-86.47706	-9.18186
loc_2	-226.726	22.12724	-10.25	0	-270.0973	-183.355
loc_3	153.0414	28.42004	5.38	0	97.33608	208.7468
loc_4	8.94844	35.79898	0.25	0.803	-61.22019	79.11707
shp_score	-643.986	106.2008	-6.06	0	-852.1471	-435.824
des_score	504.3561	136.5358	3.69	0	236.7358	771.9764
sev_score	171.5263	150.9239	1.14	0.256	-124.2957	467.3482
num_sellers	4.607997	0.224968	20.48	0	4.167043	5.048951
_cons	-1904.56	85.43933	-22.29	0	-2072.03	-1737.1

Table 11. Number of sellers for a certain type of storage, RAM, screen size OS, brand and month

This shows that while there may have been some effect on how many sellers were driven out due to competition, a potential increased demand shock may have had a stronger effect and hence, actually increased the number of sellers during a certain period.

One explanation for the phenomenon of driving out competition can be said to be the cross-selling capabilities of sellers and loss leader pricing (Li, 2013). Essentially, to increase the sales of low demand products, sellers with higher cross selling capabilities have been known to adopt loss leader pricing on products with higher demand (Li, 2013). Since sellers with lower cross selling capabilities do not have the incentive to engage in similar practices, when there is a demand shock, the price difference between the two group widens even more (Li, 2013).

On to the demand side, the increase in demand can be explained by the fact that Nokia launched a new tablet in China in November 2014 (Woollatson, 2014). Besides that, the Chinese

New Year, which occurred on January 31st 2014 ("Chinese New Year"), could also have brought the spike in demand, which could have been stronger than the competition effects on sellers and may have actually increased the number of sellers in the market, instead of the competition driving some out.

This helps us conclude that while product characteristics help identify the level of competition in the market, the strongest indication however, may be the time of the year being studied since that had the strongest effect on the variable. Lastly, the variable also had an effect on the R-squared, changing it to 73.97%, which means that almost 74% of the price of the product was due to the product characteristics, seller characteristics and market variables.

The last regression was run with the intention to see how much the characteristics of a product affected its availability in the market and in turn, the price. Although it seems similar to the variable num_sellers, it measures something slightly different and has some few components. Hence, to measure that, another variable called product characteristics, denoted by pro_char, defined as product characteristics, was created and more characteristics were added at every step. The first attribute to be added, chosen at random, was "screen", or the screen size of the tablet. As a result, the R-squared went up slightly from the initial level of 73.97% to 74.03% (Table 12).

Table 12. Products in market of a certain screen size.

					R-squared	0.7403
tot_price	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
storage	27.22184	0.172944	157.4	0	26.88285	27.56082
ram	23.97331	2.251604	10.65	0	19.56	28.38662
screen	318.0952	5.585994	56.95	0	307.1463	329.0442
os_1	-102.772	41.29051	-2.49	0.013	-183.7039	-21.8391
os_2	1195.446	86.86985	13.76	0	1025.174	1365.717
os_3	-344.541	41.74864	-8.25	0	-426.3709	-262.71
mktage	69.5633	11.55856	6.02	0	46.90767	92.21893
loc_1	-47.6296	19.69428	-2.42	0.016	-86.23186	-9.02738
loc_2	-226.51	22.10127	-10.25	0	-269.8305	-183.19
loc_3	154.195	28.3871	5.43	0	98.55421	209.8358
loc_4	13.64748	35.76286	0.38	0.703	-56.45036	83.74532
shp_score	-646.184	106.0765	-6.09	0	-854.1012	-438.266
des_score	512.4994	136.3801	3.76	0	245.1843	779.8145
sev_score	165.5074	150.7489	1.1	0.272	-129.9716	460.9864
num_sellers	5.055098	0.233102	21.69	0	4.598201	5.511994
pro_char	-0.02957	0.0041	-7.21	0	-0.0376018	-0.02153
_cons	-1664.93	91.5816	-18.18	0	-1844.437	-1485.42

Table 12. Products in market of a certain screen size

As more variables were added, like os_1, os_2, and os_3, corresponding to different operating softwares, the R-squared changed slightly but at the end, returned to almost 74% again. Interestingly, the variable was significant until the first operating software, os_1, was added to it. It also had a negative coefficient implying that an increase in the number of tablets with the same screen size reduced the price of the product itself. The variable continued to have a negative coefficient as well as being statistically insignificant with a P-value significantly higher than 0.05 until the third operating software, os_3, was added to it after adding the first two (Table 13).

Table 13. Product in the market of a certain screen size and operating software

					R-squared	0.7397
tot_price	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
storage	27.41374	0.172564	158.86	0	27.0755	27.75198
ram	24.32207	2.253694	10.79	0	19.90467	28.73948
screen	327.982	5.78003	56.74	0	316.6528	339.3113
os_1	-90.6925	41.58965	-2.18	0.029	-172.2113	-9.17375
os_2	1221.215	87.05341	14.03	0	1050.584	1391.846
os_3	-361.261	41.92653	-8.62	0	-443.4397	-279.082
mktage	67.60359	11.58625	5.83	0	44.89368	90.3135
loc_1	-48.3948	19.716	-2.45	0.014	-87.03961	-9.74998
loc_2	-225.308	22.13103	-10.18	0	-268.686	-181.929
loc_3	152.9504	28.41628	5.38	0	97.25237	208.6484
loc_4	10.57407	35.79969	0.3	0.768	-59.59594	80.74409
shp_score	-642.05	106.1893	-6.05	0	-850.1891	-433.912
des_score	503.1057	136.5186	3.69	0	235.5193	770.6921
sev_score	171.2885	150.9039	1.14	0.256	-124.4942	467.0713
num_sellers	4.80578	0.237457	20.24	0	4.340348	5.271212
pro_char	-0.01307	0.005028	-2.6	0.009	-0.022927	-0.00322
_cons	-1825.67	90.65829	-20.14	0	-2003.368	-1647.97

Table 13. Product in the market of a certain screen size and operating software

A somewhat significant increase was observed again when storage was added to the regression, resulting in the R-squared rising from about 73.89% to 73.97%. Since the P-value was 0.011, it was hence also considered statistically significant. This implies that the storage of a tablet affects the price of the product more than factors like operating software.

Since the RAM of a product affects not only how fast the device is but also the overall performance, it was expected to have a significant effect on the price ("Why is RAM so Important"). Hence, in line with expectations, when RAM was added to the equation, the R-squared increased from 73.97% to 74.03% (Table 14). Not only that, when the brand factor was added to the equation, the R-squared increased significantly from 74.03% to about 74.11%, one of the largest increases observed (Table 15).

Table 14. Product in the market of a certain screen size, operating software, storage and RAM

					R-squared	0.7403
tot_price	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
storage	27.38398	0.171688	159.5	0	27.04746	27.7205
ram	23.57278	2.25438	10.46	0	19.15403	27.99153
screen	323.4557	5.32684	60.72	0	313.0147	333.8967
os_1	-91.8854	41.3218	-2.22	0.026	-172.8792	-10.8916
os_2	1213.757	86.73405	13.99	0	1043.752	1383.762
os_3	-365.266	41.78014	-8.74	0	-447.1585	-283.374
mktage	62.75665	11.55156	5.43	0	40.11474	85.39857
loc_1	-42.0205	19.71294	-2.13	0.033	-80.6593	-3.38167
loc_2	-223.524	22.1074	-10.11	0	-266.8557	-180.192
loc_3	152.9681	28.38849	5.39	0	97.32459	208.6116
loc_4	8.051581	35.75947	0.23	0.822	-62.0396	78.14276
shp_score	-629.634	106.1026	-5.93	0	-837.6032	-421.665
des_score	485.5258	136.4107	3.56	0	218.1508	752.9008
sev_score	175.7719	150.7576	1.17	0.244	-119.7241	471.2678
num_sellers	5.367541	0.249454	21.52	0	4.878593	5.856489
pro_char	-0.08575	0.012227	-7.01	0	-0.1097154	-0.06178
_cons	-1762.07	87.72974	-20.09	0	-1934.023	-1590.11

Table 14. Product in the market of a certain screen size, operating software, storage and RAM

Notably though, the coefficient of the variable “Pro_char” remained negative until the brand factor was taken into consideration. Hence, it can be implied that while having too many similar products may bring down the price, differentiating them through brands may in fact drives the prices higher (Table 15).

Table 15. Product in the market of a certain screen size, operating software, storage, RAM and brand

					R-squared	0.7411
tot_price	Coef.	Std. Err.	t	P>|t|	[95% Conf. Interval]	
storage	27.26331	0.171672	158.81	0	26.92682	27.5998
ram	24.37459	2.24682	10.85	0	19.97066	28.77852
screen	341.5196	5.077399	67.26	0	331.5675	351.4717
os_1	-90.207	41.23798	-2.19	0.029	-171.0365	-9.37751
os_2	1281.231	86.57932	14.8	0	1111.529	1450.933
os_3	-326.318	41.73156	-7.82	0	-408.1144	-244.521
mktage	61.54892	11.53083	5.34	0	38.94763	84.1502
loc_1	-79.4301	19.86654	-4	0	-118.37	-40.4903
loc_2	-230.182	22.06716	-10.43	0	-273.4349	-186.928
loc_3	155.4844	28.34091	5.49	0	99.93412	211.0346
loc_4	15.23325	35.70271	0.43	0.67	-54.74668	85.21319
shp_score	-642.153	105.902	-6.06	0	-849.7286	-434.577
des_score	511.034	136.1529	3.75	0	244.1643	777.9037
sev_score	163.1021	150.5011	1.08	0.278	-131.891	458.0953
num_sellers	-3.75604	0.785448	-4.78	0	-5.295577	-2.21651
pro_char	1.359913	0.122387	11.11	0	1.120026	1.5998
_cons	-1959.73	85.34342	-22.96	0	-2127.011	-1792.45

Table 15. Product in the market of a certain screen size, operating software, storage, RAM and brand

From the data, hence, we can safely conclude that while some factors, like the operating software, storage, screen size etc. affect the price of the product to a moderate amount, the central element about a tablet that explains the price is the brand.

Similar results were also replicated in a study done which concluded that not only is the brand affect more prominent online than offline, but also that people online are less sensitive to price effects and promotions than people offline (Degeratu, 2000). However, this is contingent on the amount of information that is available about the product. When more information is provided, brand name becomes less relevant (Degeratu, 2000).

Hence, it is safe to conclude that characteristics of a product affect not only the price of the product but also its presence in the market itself, which in turn affects the price as well.

Discussion:

While we would expect the internet to behave like a perfect competition, that is not what is observed in reality. This may occur due to various reasons. For starters, it has been shown that websites have a rather steep learning curve (Ratchford, 2009). This means that the duration of visit to a website decreases when one visits it more often. As a result, the time required to complete a transaction on a familiar website is lower than on an unfamiliar website (Ratchford, 2009). Hence, the familiar website has a cost advantage, creating a lock in effect. Another possible explanation for the prevalence of inconsistent pricing may be due to the risk involved with shopping online. It has been shown that even when consumers can see lower prices, they tend to not buy from them (Smith et.al, 2001). It has been shown that since consumers cannot physically inspect the product in consideration, have to pay before receiving goods and cannot resolve issues in person, they prefer sellers with higher ratings and credibility (Smith et.al, 2001). Lastly, researching prices online involves what is known as search costs. It has been shown that when search costs are homogenous and prices are a function of a firm's marginal costs, high cost firms have lower shares and higher prices while low cost firms have higher market share and lower prices. Hence, the existence of price dispersion can also be due to heterogeneous search costs and varying marginal costs for firms and vice versa (Carlson et.al, 1983).

While there have been many studies done in the field of price dispersion, there still are not enough studies done in the area of online price dispersion. This may be because of the fact that the internet is still a relatively new phenomenon. Besides that, even lesser studies have tried to break down the price of a product and decipher the amount of price dispersion that is prevalent. This study hence, hopes to contribute to the field by breaking down price and trying to find how much of the price is defined just by the dispersion.

Conclusion:

Economists have acknowledged, explored and studied the presence of price dispersion intensively. The creation of internet unexpectedly gave rise to a new form of price dispersion-online price dispersion. Many have studied this relatively new phenomenon and reached various conclusions. This study aimed to break down the price of electronic tablets being sold on an online platform and to decipher what percentage of the price could be explained by product characteristics, seller characteristics and market variables. It was found that product characteristics by themselves explained a little less than 73% of the price while seller characteristics, by themselves, could explain just over 1% of the price. When market variables were taken into account, like the number of sellers selling the same product or how the product characteristics affected its availability, the number jumped to around 74.11%.

Hence, it can be concluded that 74.11% of the price of a product is due to measurable factors. The rest is due to the price dispersion, which could be due to various factors. Since finding out the true cause of this dispersion is infeasible, it can be attributed to varying causes, like search costs. the risks shoppers face with online shopping or even due to varying marginal costs of sellers etc.

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EDUCATION

The Pennsylvania State University — Graduation: May'19
Schreyer Honors College
Paterno Fellows Program in College of Liberal Arts
B.S (Hons) Economics and B.S Finance — Dean's list: Fall'15-Spring'18

WORK EXPERIENCE AND TECHNICAL SKILLS

Summer Intern — May'17-June-17
EY, Transfer Pricing (India)

- Assisted the manager to better understand the potential client's company structure and expand the existing USD198bn Indian client base.
- Optimized databases to provide assistance about client's competitor to find arm's length price for tax purposes.

Summer Intern — May'16-July'16
AU Financiers (India) Ltd.

- Analyzed and presented the implication on the current client base if the NBFC were to turn into a bank.
- Examined and assisted potential clients with paperwork and checking collateral for loans worth up to Rs.200,000.

Research Assistant (and co-author) — July'17-August'17
The Pennsylvania State University, Dept. of Economics

- Developed and optimized existing models on trade blocks using MATLAB and Stata to benefit current research.

Joint Head Teaching Assistant — August'16-May'17
The Pennsylvania State University, Dept. of Economics

- Evaluated assignments and examinations, proctored exams and in class activities.
- Mediator between students and professor ensuring smooth functioning.

Technical skills: MATLAB, Stata, Python, C, Microsoft Office

LEADERSHIP POSITIONS AND EXTRACURRICULARS

International Horse Shows May'13-October'14
Dressage Rider

· Represented India as the youngest rider ever at 2014 Asian Games, and other international events.

· Qualified for the final selection round of 2016 Olympics.

National Society of Collegiate Scholars Jan'18-Present
President
Penn State

· Doubled attendance and participation by reaching out to other clubs, holding info sessions etc.

Liberal Arts Undergraduate Council Jan'18- Present
THON Chair
Penn State

· Raised 800USD through local fundraisers and online platforms in two months.

· Arranging canvassing and canning trips and online donation drives for future fundraising.

Penn State Dressage Club Aug'16-May'17
Secretary

· Conducted meetings, managed attendance and ensured undisturbed intra-club communication.