Price Setting in Online and Offline Markets: Evidence from Korea*

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Abstract

We empirically examine price levels, price stickiness, and price dispersion in online markets using data provided by a South Korea's leading multinational conglomerate corporation with department stores, supermarkets, drugstores, electronics stores, and convenience stores under its umbrella. Our dataset is unique in that it allows us (1) to compare the offline and online prices of the same product sold by the same retail company, (2) to distinguish between the list price (i.e., the price displayed in the offline storefront or on the online store screen) and the transaction price (i.e., the price actually paid by the customer) of a particular product, and (3) to calculate a weighted average of individual prices (e.g., cost of living indexes) using the corresponding sales amount as weights. Our main findings are as follows. First, we show that online prices tend to be lower, more flexible, and less dispersed than offline prices. Second, the difference between transaction and list prices, which we refer to as "personalized discounts," are, on average, larger for online transactions than for offline transactions, and its dispersion across transactions is also larger for online transactions. Third, we provide evidence for the Amazon effect by showing that the prices of a particular product offered by various offline shops tend to converge to the corresponding online price.

JEL Classification Numbers: D22; L11; L81; O14
Keywords: online markets; offline markets; price stickiness; price dispersion; personalized discounts; temporary sales; Amazon effect

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1 Introduction

Consumer purchasing has been shifting from offline to online markets in many countries. In macroeconomic studies, it has been argued that online markets are characterized by lower operating costs, lower menu costs, lower search costs, and lower costs of monitoring competitors' prices than the offline markets, which may lead to lower and more flexible prices and a reduction in price dispersion among regions/retailers.

This paper aims to empirically examine the impact of the spread of online transactions on price levels and price stickiness and analyze its implications for the macroeconomy.

We employ a unique scanner data provided by a South Korea's leading multinational conglomerate corporation, with department stores, supermarkets, drugstores, electronics stores, convenience stores, etc., under its umbrella. This dataset is unique in the following respects. First, all subsidiary companies sell their products through both offline and online channels, which allows us to compare the offline and online prices for the same product sold by the same company.

Second, the dataset contains both list and transaction prices. Specifically, it contains information on customer/transaction-specific price discounts, which we refer to as "personalized discounts." In our dataset, personalized discounts are observed in both online and offline markets but are more common in online markets. On the other hand, uniform discounts (i.e., discounts uniformly applied to all customers) like temporary sales are more common in offline markets. Previous studies on price level comparison, price stickiness, and price dispersion in online markets typically use list prices rather than transaction prices, thus not paying attention to the role of personalized discounts. In this paper, we look at both list prices and transaction prices to see to what extent the results would differ between using list prices and transaction prices.

The rest of the paper is organized as follows. Section 1 explains the dataset we use in this paper. Section 2 compares price levels between offline and online markets. Section 3 estimates the frequency and size of price adjustments for offline and online prices. Section 4 estimates price dispersion across customers, as well as offline retailers. Section 5 provides a summary of our main findings and some policy implications.

Table 1: Overview of the Dataset

	Offline			
	Sample period	No. of stores	No. of products	No. of records
Supermarket	Jan 2014-Jun 2019	733	103,258	1,694,428,735
Drugstore	Feb 2015-Jun 2019	138	30,972	33,461,045
Electronics store	Jun 2016-Jun 2019	494	48,335	13,075,131
Convenience store	Jan 2014-Jun 2019	12,799	—	223,496,284
	Online			
	Sample period	No. of stores	No. of products	No. of records
Supermarket	Jun 2016-Jun 2019	1	27,896	47,655,404
Drugstore	Jun 2017-Jun 2019	1	10,042	577,090
Electronics store	Jun 2016-Jun 2019	1	25,692	227,399
Convenience store	—	0	0	0

2 Data

2.1 Overview

The data we use in this paper is provided by a South Korea's leading multinational conglomerate corporation. This corporation has several retail companies under its umbrella, including supermarkets, drugstores, electronics stores, convenience stores, and online shopping malls. For example, the supermarket company has 733 offline stores and one online store (see Table 1). Similarly, the drugstore company and the retail electronics company sell through both online and offline channels. In contrast, convenience stores sell only offline, and online shopping malls sell only online.

When a customer of this corporation purchases at one of these companies, it is recorded as data with a personal ID. It is this data that we use in this paper. In this paper, we mainly use data from three companies that sell both offline and online: the supermarket company, the drugstore company, and the retail electronics company.

This dataset has the following features. First, it is possible to compare offline and online prices of the same product sold by the same company. For example, when comparing offline and online prices of products sold in supermarkets, the two prices are those offered by a single supermarket company. Previous studies on the comparison of online and offline prices have compared online and offline prices for a particular product, but the companies offering the two prices were typically different. Therefore, the difference between offline and online prices detected in the data may stem from differences between the two companies, such as

Table 2: Number of Products Available in Online and Offline Markets

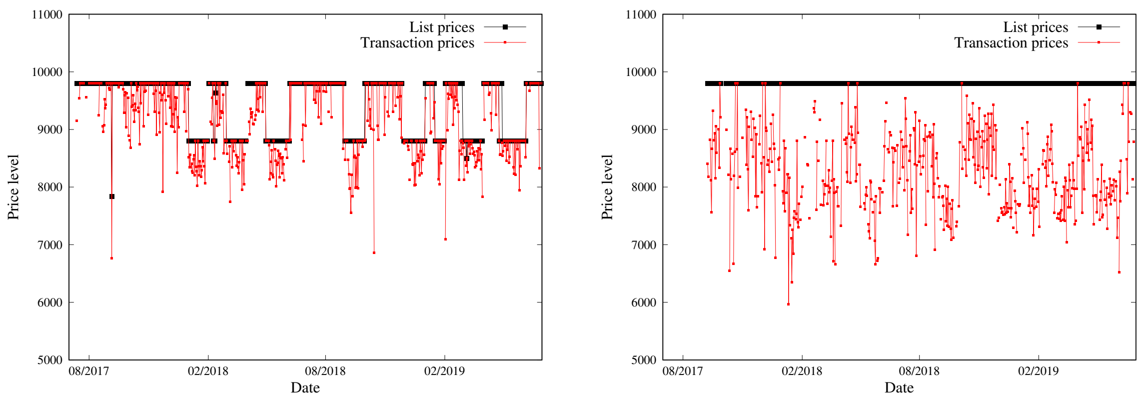
	Available both offline and online	Available only offline	Available only online	Sold offline and online on the same day
Supermarket	0.334	0.630	0.036	0.115
Drugstore	0.457	0.542	0.010	0.061
Electronics store	0.103	0.617	0.280	0.011

Note: The column labeled "Sold offline and online on the same day" shows the probability that a particular good is sold (and purchased by at least one customer) on a particular day both in offline and online markets.

differences in financial resources of the companies that could determine how much discounting the companies can afford to implement. In our dataset, as offline and online prices are determined by a single company, we do not worry about the possibility that the difference between offline and online prices comes from differences between the companies.

The second feature of our dataset is that it records both "list prices," which is the price displayed in the offline storefront or on the online store screen, and "transaction prices," which is the price paid by the customer. The difference between the two is personalized discounts, where each customer receives a different discount (See, for example, Dubé and Misra (2019) for personalized discounts). For instance, in an online store, coupons distributed to customers via the Internet allow them to purchase items at a price lower than the list price displayed on the screen. Coupons are not necessarily distributed to all customers, and the discount rate varies among customers to whom the coupons are distributed. Whether or not coupons are given out, and if so, the discount rate, depends partly on the customer's attributes such as age and gender and partly on the customer's past purchase history. Previous studies on the comparison of offline and online prices have typically used list prices and thus have not examined the extent to which personalized discounts contribute to the difference between offline and online prices, such as which price is lower, offline or online, and which price is more flexible (see, for example, Cavallo (2017, 2018), Gorodnichenko and Talavera (2017), and Gorodnichenko et al. (2018)). In this paper, we address similar questions as the previous studies but use both list prices and transaction prices, thereby contributing to the literature by making clear the role of personalized discounts in online price settings.

Figure 1: Offline and Online Prices of a Skincare Product



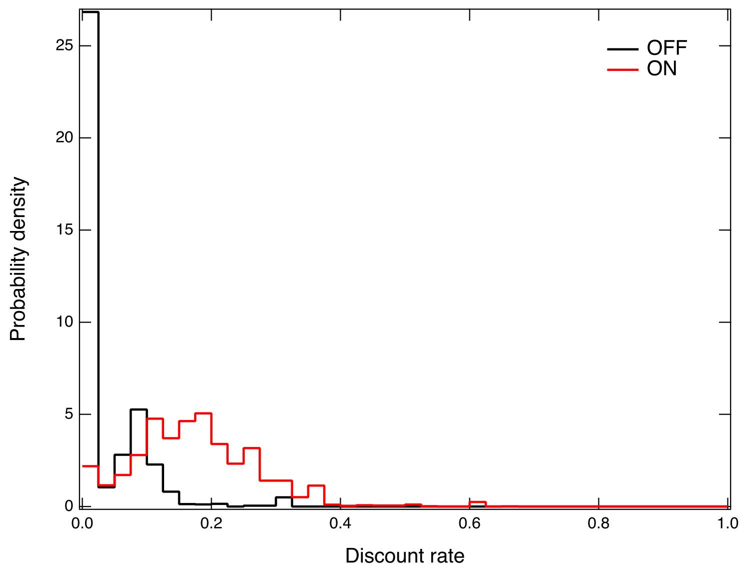
Note: The left panel shows the price of a particular skincare product sold at a particular offline shop, while the right panel shows the price of the same product sold at an online shop. The black and red lines represent the list and transaction prices.

2.2 Example

Figure 1 shows how the price of a specific skincare product sold by the drugstore company has changed over time. The left panel shows the price at an offline store, and the right panel shows the price at an online store. In both figures, the black line represents the list price, and the red line represents the transaction price.

The figure shows the following about the difference between offline and online pricing. First, the left panel shows that there were eight temporary sales during this period in this offline store. The discount rate for each sale looks the same, about 10 percent. On the other hand, we do not see any temporary sales in the right panel. Varian (1980) argues that sellers can use temporary sales to discriminate between customers with high and low price elasticities. Customers with high price elasticity spend more time searching for low prices due to temporary sales, while customers with low price elasticity do not do that. Therefore, customers with high price elasticity tend to go shopping during temporary sales, while customers with low price elasticity typically buy on days when stores sell at regular prices. In this way, sellers can discriminate between the two types of customers. However, it is often argued that the search cost is much smaller or even negligible in online markets, so sellers cannot use temporary sales as a means to achieve price discrimination. This might explain why we do not see any temporary sales in the right panel.

Figure 2: Personalized Discount Rates of a Skincare Product



Note: The black line shows the histogram of personalized discount rates of a particular skincare product at a particular offline shop over the entire sample period. The red line shows the corresponding histogram at an online shop.

Second, the transaction price shown by the red line in the right panel is much lower than the list price, which is shown by the black line, in most periods, indicating that the extent of personalized discounts is non-negligible. To compare the personalized discount rates between offline and online transactions, Figure 2 shows the histograms of the discount rates applied, online and offline, to the same skin care products as in Figure 1. It shows that discount rates at the offline store are low, rarely exceeding 10 percent. In contrast, discount rates in the online store are much larger, with the mode of the distribution being 20 percent and sometimes exceeding 30 percent. To make sure that this feature is not specific to this particular skincare product, we calculate the mean and standard deviation of personalized discount rates for all products sold in supermarkets and drugstores. Table 3 shows that personalized discount rates are, on average, greater in online markets and that the dispersion of personalized discount rates across transactions is also greater in online markets.

Third, the right panel of Figure 1 shows that online list prices are highly sticky. In contrast, offline list prices in the left panel are much less sticky, presumably reflecting that offline list prices often change due to temporary sales. However, if we focus on transaction prices rather

Table 3: Personalized Discount Rates

	Offline		Online	
	Mean	Std Dev	Mean	Std Dev
Supermarket	0.0227	0.0346	0.0639	0.0412
Drugstore	0.0764	0.0489	0.3341	0.1473

Notes: The personalized discount rate for a particular transaction is defined as the percentage discount of the transaction price for that transaction from the corresponding list price. The figures in the table represent the mean and the standard deviation of personalized discount rates across all transactions.

than list prices, the opposite holds; online prices look more flexible than offline prices. As we saw in Figure 2 and Table 3, there are large *cross sectional* differences in the personalized discount rates. Still, there are also large differences in the average of personalized discount rates *over time*. Note that transaction prices are volatile even at offline stores but less so than at online stores. These observations suggest that, when discussing price stickiness/flexibility in online markets, it may be inappropriate to focus only on list prices as previous studies did. In the next section, we will pay attention to both list and transaction prices when examining price stickiness.

2.3 Relationship between list prices and transaction prices

List prices and transaction prices are closely related, as seen in Figure 1, but sometimes exhibit substantial deviations. How are they related over time? To address this, we run a simple regression using the percentage change in the transaction price of a particular product on a given day from the previous day as the dependent variable and the corresponding percentage change for the list price as the independent variable.

The regression results are shown in Table 4. First, for supermarkets, the coefficient on the list price is 0.989 for offline prices and 0.999 for online prices, both close to 1. This means that when the list price of a particular product changes by 1 percent, the corresponding transaction price changes, on average, by about 1 percent. However, the adjusted R2 presented in the table is 0.741 offline and 0.868 online, indicating that a non-negligible portion of the change in transaction prices is left unexplained by changes in list prices. In other words, a certain portion of the change in transaction prices over time is due to changes in personalized discounts (more precisely, changes in the average value of personalized discounts across transactions).

Table 4: Regression of Transaction Prices on List Prices

	Supermarket		Drugstore	
	Offline	Online	Offline	Online
Coefficient on list prices	0.989	0.999	0.942	0.614
	(0.000)	(0.000)	(0.001)	(0.088)
Constant term	-0.001	0.000	0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)
No. of Observations	169,939,504	3,248,357	2,880,081	81,401
Adjusted R2	0.741	0.868	0.146	0.001

Notes: The personalized discount rate for a transaction is defined as the percentage discount of the transaction price for that transaction from the corresponding list price. The figures in the table represent the mean and the standard deviation of personalized discount rates across transactions.

Second, turning to the result for drugstores, the coefficient on list price is 0.942 for offline and 0.614 for online, both deviating from 1, with a particularly large deviation for online. As for adjusted R2, it is 0.146 for offline, and 0.001 for online, and both are very low. In other words, changes in transaction prices can hardly be explained by changes in list prices, indicating that changes in transaction prices over time are mostly attributed to changes in personalized discounts over time.

3 Are prices lower in online markets than in offline markets?

Table 5 compares prices in offline and online markets. Specifically, products sold in both online and offline markets are extracted, and a bilateral comparison is made between the price of a particular product at a particular offline store on a particular day and the price of the same product at the online store on the same day. The upper panel shows the results for list prices, while the lower panel for transaction prices.

First, the result for list prices shows that the probability of prices being identical in offline and online markets is 71.5 percent for supermarkets and 31.4 percent for drugstores, both of which are high. Here, "identical price" is defined as that the price difference is less than 10 Korean won or 0.01 US dollars. These results are consistent with the findings reported in previous studies, such as Cavallo (2017), which are based on the data from the US and other industrial countries. Turning to the cases in which price differences exceed 10 won, online prices tend to be lower for supermarkets. Specifically, the probability that online prices are

Table 5: Price Level Comparison

	List prices				
	Identical	Higher online	Lower online	Online markup	Online difference
Supermarket	0.715	0.077	0.208	-0.094	-0.027
Drugstore	0.314	0.686	0.000	0.412	0.283
	Transaction prices				
	Identical	Higher online	Lower online	Online markup	Online difference
Supermarket	0.594	0.145	0.261	-0.035	-0.014
Drugstore	0.066	0.089	0.845	-0.217	-0.203
Electronics store	0.189	0.096	0.715	-0.090	-0.073

Notes: “Identical” is defined as that the difference between the online and offline prices for a particular product on a particular day is less than 10 South Korean Won, which is about 0.01 US dollars. The column labeled “Online markup” represents the average of the log differences between online and offline prices for all products except for those products with identical prices. The column labeled “Online difference” represents the average of the log differences between online and offline prices for all products.

lower than offline prices is 20.8 percent, while the probability for the opposite case is only 7.7 percent. As shown in the column labeled “Online markup”, online prices are, on average, 9.4 percent lower than offline prices. However, for drugstores, online prices tend to be higher than offline prices (i.e., 0 percent probability that online prices are lower than offline prices versus 68.6 percent vice versa). As the “Online markup” column shows, online prices for drugstores are, on average, 41.2 percent higher than offline prices. Thus, the table indicates that online prices are not always lower as far as list prices are concerned.

However, we obtain a different result when we turn to transaction prices. First, the probability that transaction prices are identical between online and offline is 59.4 percent for supermarkets and 6.6 percent for drugstores, both of which are much lower than the corresponding probability for list prices. On the other hand, the probability of lower online prices is 26.1 percent for supermarkets and 84.5 percent for drugstores, which is much higher than the corresponding probability for list prices. Noteworthy for the result for drugstores; the probability of having a lower online price was 0 percent for list prices, but it increases to 84.5 percent for transaction prices. As shown in the “Online markup” column, online prices are, on average, 3.5 percent lower than offline prices in supermarkets and 21.7 percent lower in drugstores. In electronic stores, too, online prices tend to be lower than offline prices.

Table 6: Frequency of Price Changes: All Goods

	List prices			
	Offline		Online	
	Increase	Decrease	Increase	Decrease
Supermarket	0.063	0.064	0.110	0.104
Drugstore	0.009	0.010	0.031	0.030
Convenience store	0.055	0.055		
Online shopping mall			0.002	0.013
	Transaction prices			
	Offline		Online	
	Increase	Decrease	Increase	Decrease
Supermarket	0.116	0.119	0.150	0.142
Drugstore	0.210	0.211	0.482	0.470
Electronics store	0.094	0.114	0.249	0.258
Convenience store	0.055	0.055		
Online shopping mall			0.252	0.176

Notes: "Increase" represents the probability that the price of a particular good at a particular day is adjusted upward from the price in the day before. "Decrease" is defined similarly.

4 Are prices less sticky in online markets than in offline markets?

4.1 Frequency of price adjustments

Table 6 compares the probability of price adjustments in offline and online markets. Specifically, the probability that today ' s price for a particular product differs from the price yesterday for that product is calculated separately for cases where the price is adjusted upward and downward.

First, the result for list prices in the upper panel shows that the probability of price adjustments for offline supermarkets is 0.06, while the corresponding probability for online supermarkets is 0.10, indicating that prices are more flexible in online markets. Similarly, for drugstores, the probability of price adjustments is 0.01 for offline prices versus 0.03 for online prices, indicating that prices are more flexible in online markets. These results are consistent with previous studies, such as Gorodnichenko and Talavera (2017) and Gorodnichenko et al. (2018).

Next, the result based on transaction prices, presented in the lower part of the table,

Table 7: Frequency of Price Changes: Goods Available both Online and Offline

	List prices			
	Offline		Online	
	Increase	Decrease	Increase	Decrease
Supermarket	0.049	0.050	0.107	0.100
Drugstore	0.010	0.010	0.000	0.003
	Transaction prices			
	Offline		Online	
	Increase	Decrease	Increase	Decrease
Supermarket	0.109	0.112	0.150	0.142
Drugstore	0.233	0.233	0.482	0.470
Electronics store	0.097	0.114	0.249	0.258

onduct [c]p31zw Notes: "Increase" represents the probability that the price of a particular good at a particu

shows that the probability of price adjustments is significantly higher for both supermarkets and drugstores, indicating that transaction prices are much more flexible than list prices. This tendency is particularly pronounced for drugstores, where the probability of price adjustments for offline transactions is 0.01 for list prices versus 0.21 for transaction prices. The same tendency is observed for online transactions, where the probability of price adjustments is 0.48 for transaction prices, which is much higher than the corresponding figure for list prices (0.03). The higher frequency of price adjustments for transaction prices is also seen in electronics stores. These results suggest that personalized discounts, which are included in transaction prices, play a crucial role in determining price stickiness.

In sum, the probability of price adjustments is higher in online markets, and it is higher for transaction prices relative to list prices. To check the robustness of these two results, we first conduct the same calculations as in Table 6, restricting them to products sold in both online and offline markets. As shown in Table 7, the result is the same as in Table 6, which was based on all products.

Next, we calculate the probabilities of price adjustments for individual products as before and then aggregate them using the sales amount of each product as weights. Note that this differs from unweighted aggregation in Tables 6 and 7. The result shown in Table 8 is the same as in Tables 6 and 7. However, compared to Tables 6 and 7, the probability of price adjustments is, in general, higher in Table 8, suggesting that the probability of price adjustment is higher for mainstay products with large sales amounts than for other products.

Table 8: Frequency of Price Changes: Weighted Average Based on Sales

	List prices			
	Offline		Online	
	Increase	Decrease	Increase	Decrease
Supermarket	0.103	0.107	0.184	0.191
Drugstore	0.012	0.013	0.000	0.003
	Transaction prices			
	Offline		Online	
	Increase	Decrease	Increase	Decrease
Supermarket	0.183	0.191	0.335	0.321
Drugstore	0.278	0.279	0.490	0.481
Electronics store	0.194	0.247	0.287	0.299

Notes: The probabilities of price adjustments for individual products are calculated for those products available both online and offline. The probabilities for individual products are aggregated using the sales amount of individual products as weights.

It should be noted that previous studies on price stickiness in online markets, such as Cavallo (2017), do not conduct weighted aggregation simply because the sales amount of individual products was not available. To cope with this issue, Gorodnichenko et al. (2018) use the number of clicks as a proxy to the sales amount. Our result shown above suggests that unweighted aggregation may not be appropriate as it leads to an overestimation of price stickiness.

4.2 Average size of price adjustments

Table 9 compares the average size of price adjustments between offline and online markets. The comparison here is limited to products sold in both offline and online markets. In addition, sales of each product are used as weights when aggregating the size of price adjustments for each product.

As we saw in Table 8, prices are generally more flexible in online markets. If we interpret this fact as meaning that adjustments to the appropriate price level occur more frequently in online markets, the size of each price adjustment should be smaller. For example, according to the menu cost theory, as menu costs become smaller, price adjustment occurs more frequently, while the size of each price adjustment becomes smaller.

Table 9 shows that the size of price adjustments for supermarket transaction prices is

Table 9: Average Size of Price Changes

	List prices			
	Offline		Online	
	Increase	Decrease	Increase	Decrease
Supermarket	0.206	0.211	0.061	0.062
Drugstore	0.201	0.200	0.213	0.298
	Transaction prices			
	Offline		Online	
	Increase	Decrease	Increase	Decrease
Supermarket	0.160	0.168	0.102	0.110
Drugstore	0.089	0.090	0.132	0.131
Electronics store	0.091	0.119	0.034	0.035

Notes: The average size of price adjustments for individual products is calculated for those products available both online and offline. The average size of price adjustments for individual products is aggregated using the sales amount of individual products as weights.

smaller in online markets, which is consistent with the above prediction. In other words, smaller and more frequent price adjustments occur in online markets than in offline markets. A similar tendency can be observed for transaction prices in electronics stores.

However, for drugstores, the size of price adjustments is larger in online markets for both list and transaction prices. The larger size of price adjustments for list prices is not unnatural since the probability of price adjustments for list prices is lower in online markets, as we saw in Table 8. However, for transaction prices, since the probability of price adjustments is higher in online markets, the size of price adjustments should be smaller in online markets, but this is not the case. This result is inconsistent with the menu cost theory, suggesting that a higher probability of price adjustments in online markets may not necessarily mean a faster adjustment to the appropriate price level.

5 Are prices closer to the law-of-one-price in online markets than in offline markets?

5.1 Price dispersion across customers

In offline markets, it is not easy to gather information on which products are sold at what price in which stores. Moreover, even if such information is available, if the store selling something at a low price is located far away, the cost of travel to get there is nontrivial. Consumers do not necessarily buy at the store that sells at the lowest price due to information acquisition and traveling costs. In contrast, in online markets, it is easier to gather information about the price of a product. In addition, there is no need to travel to the store physically. Under these circumstances, it is often argued that every consumer would buy at the store that sells at the lowest price, and therefore the dispersion in purchase prices among consumers should be significantly reduced or even disappear.

To see whether purchase prices in online markets are identical across consumers, we calculate the price paid by a given consumer for a given product in a given month and then calculate the standard deviation of those prices across consumers. We repeat the same calculations for all products. Table 10 shows the average of the standard deviations for individual products calculated in that way.

First, for list prices, the price dispersion in online markets, while not zero, is much smaller than the corresponding price dispersion in offline markets. This result is consistent with the hypothesis mentioned above.

Turning to transaction prices, the price dispersion is smaller online than offline as far as supermarkets and electronic stores are concerned. Still, the price dispersion for drugstores is greater online than offline. This may reflect that personalized discount rates applied to online purchases vary substantially among consumers. In online markets, sellers can easily collect information about consumer attributes and past purchase history and use this information to offer different prices to each consumer. The above result for drugstores suggests that this may impede the law-of-one-price in online markets.

Table 11 uses each consumer's purchase price calculated in Table 10 to calculate the purchase price of consumers living in a given region and how much it varies across regions. Again, we can see that the dispersion of online list prices is smaller than that of offline list prices. However, when we turn to transaction prices, we find that, for drugstores, the online price dispersion is greater. Suppose the attributes and past purchase histories of consumers in one region are not that much different from those of consumers in another region, then, even if there are differences in purchase prices among consumers, the price dispersion across regions should be small. However, the fact that this is not the case suggests that residents ' attributes and purchasing histories differ significantly across regions.

Table 10: Price dispersion across customers

	List price		Transaction price	
	Offline	Online	Offline	Online
Supermarket	0.144	0.085	0.171	0.096
Drugstore	0.033	0.001	0.111	0.271
Electronics store	–	–	0.085	0.035

Note: The average purchase price of a particular product in a particular month for a particular customer, which is identified by customer ID, is calculated, and then the standard deviation of the log purchase prices for that product across customers is calculated. The figures shown in the table are the average of the standard deviations across products.

Table 11: Price dispersion across regions

	List price		Transaction price	
	Offline	Online	Offline	Online
Supermarket	0.073	0.044	0.088	0.051
Drugstore	0.017	0.002	0.056	0.182
Electronics store	–	–	0.050	0.027

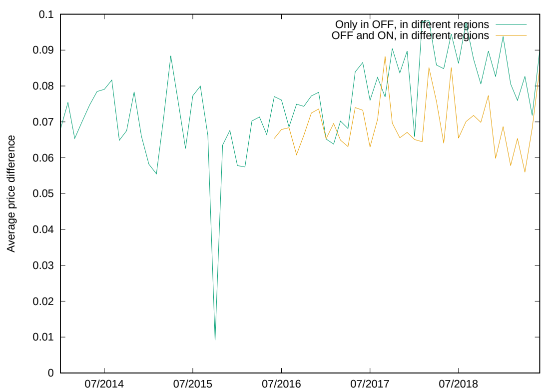
Note: The average purchase price of a particular product in a particular month for those customers who live in a particular region is calculated and then the standard deviation of the log purchase prices for that product across regions is calculated. The figures shown in the table are the average of the standard deviations across products.

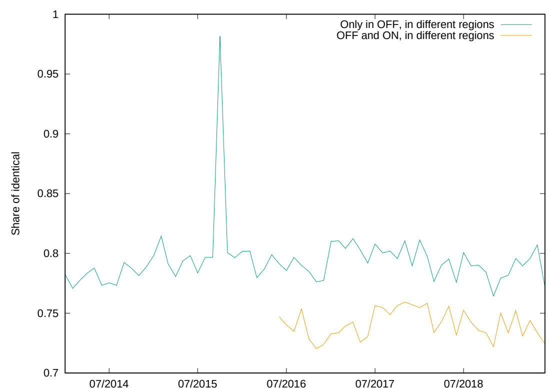
5.2 Amazon effect

It is sometimes argued that as consumers rely on online purchases more often, they would compare offline prices with online prices, and as a result, prices offered at various offline stores would converge to online prices, thus reducing the price dispersion across offline stores. This is referred to as the Amazon effect.

Although Amazon has a much lower market share in Korea than in other countries, it is possible that even in Korea, the price dispersion across offline stores has been decreasing as online penetration increases. To investigate this possibility, we conduct the following exercise closely following Cavallo (2018). First, we calculate the extent to which the list prices of any

Figure 3: Price Difference Across Offline Stores Located in Different Regions





Notes: The left panel shows the average difference between the two list prices of a particular product offered by any two offline stores located in different regions. The green line is for those products available only in offline markets, while the orange line is for those products available both in offline and online markets. The right panel shows the probability that the two list prices of a particular product offered by any two offline stores located in different regions are identical in the sense that the difference is less than 20 Korean Won, which is about 0.02 US dollars. The green line is for those products available only in offline markets, while the orange line is for those products available both in offline and online markets.

two offline stores operating in different regions differ for a given product and repeat this for all offline store combinations. Those values are then averaged to obtain an indicator of offline price dispersion for that product. Next, we classify products into those sold only offline and those sold both offline and online. The green line in the left panel of Figure 3 shows the average of the indicators of offline price dispersion calculated in the first step for products sold only offline, while the orange line shows the average of the indicators for those products sold both offline and online.

The Amazon effect should only work for goods sold both offline and online. Thus, the price dispersion should decrease for products sold in both markets. Looking at the two lines shown in the figure, there is no significant difference between the two from 2016 to 2017. However, starting in the second half of 2017, the price dispersion for products sold both offline and online, indicated by the orange line, has been declining, while the price dispersion for products sold only offline, indicated by the green line, has been increasing. As a result, the two lines exhibit a substantial divergence, suggesting that the Amazon effect may be at work in South Korea.

Is the Amazon effect resulting in the complete disappearance of price dispersion between offline stores, i.e., the establishment of the law of one price between offline prices? To address this, we calculate the probability of identical prices among offline list prices offered by stores located in different regions. The result is shown in the right panel of Figure 3; the orange line is for the result for products sold both offline and online, and the green line is for the result for products sold only offline. It indicates that the probability of "identical price" for products sold both offline and online is lower than that for products sold only offline, and has not shown any sign of increasing in recent years. Given these results, it may be true that the Amazon effect has reduced the price dispersion in offline markets to some extent, but the price dispersion has not yet entirely disappeared.

6 Tentative summary and policy implications

This paper empirically examined how the spread of online transactions has affected price levels, price stickiness, and price dispersion in online and offline markets. We employ unique data provided by a South Korea's leading multinational conglomerate corporation, with department stores, supermarkets, drugstores, electronics stores, convenience stores, etc., under its umbrella.

This dataset is unique in the following respects: (1) each company sells its products through offline and online channels, which allows us to compare the offline and online prices for the same product sold by the same company; (2) it contains both list and transaction prices, thus giving us information customer/transaction-specific price discounts, which we refer to as "personalized discounts."

Our main findings are as follows. First, online prices tend to be lower, more flexible, and less dispersed than offline prices. Second, we show that the dispersion of offline prices for those products available both offline and online is smaller than that for those products available only offline, suggesting the presence of the convergence of prices at various offline shops of a particular product to the corresponding online price only when the product is available online. This can be seen as evidence supporting the presence of the Amazon effect. Third, personalized discounts are, on average, greater for online transactions, and their dispersion across transactions is also greater for online transactions.

[To be completed]

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