THE ROLE OF FIRM SCALE AND SEARCH ENGINE OPTIMIZATION IN SHAPING PRICE DIFFERENTIALS IN THE ECOMMERCE INDUSTRY IN UKRAINE

by

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LIST OF ABBREVIATIONS

SEO Search Engine Optimization

CPM Cost Per Mille – How much an advertiser pays for 1,000 times their ad is shown (impressions)

CPC Cost Per Click **–** How much the advertiser pays each time someone clicks on their ad.

CPA Cost Per Action **-** How much the advertiser pays when a user does a defined action, like buying or signing up

CHAPTER 1. INTRODUCTION

Nowadays the role of e-commerce websites becomes more and more important for our lives, while role of online visibility becomes more and more important for e-commerce websites. Customers do not only choose between products, but also between sellers that are easier to find in search results or are known for their well-known and successfully marketed brand name.

According to Statista (2025) the revenue in the eCommerce Market is projected to reach US$2.88bn in 2025 with an annual growth rate (CAGR 2025-2030) of 4.56%, resulting in a projected market volume of US$3.59bn by 2030.

At the same time, the size of the company also plays an important role here. Large firms have more employees and more resources. This gives them the possibility to use economies of scale, because they can spread fixed marketing costs over many products and customers. On the other hand, the same resources can also give them market power, which lets them set higher prices, partly to cover big marketing expenses.

On the other side of the coin, smaller companies may have fewer resources and must find other ways to compete. It raises the question: how does company size and SEO affect the prices customers see?

My research looks at e-commerce firms and tries to connect three things: SEO as possible proxy of company marketing, number of employees as possible proxy of company scale, and the prices of products to try measure consumer welfare.

The results can give practical insights for e-commerce business owners and managers who decide how much to invest in SEO for possible better market power and pricing strategies organization for best company scale. Moreover, this research can provide insights of consumer welfare for government, who usually designs antitrust policy and should know about consumer well-being in e-commerce sector.

This study may be one of the first to examine probable relationship between company size, digital marketing, and consumer prices in the Ukrainian e-commerce market. It can be valuable for understanding of how to work in developing economies for businesses.

The research analysis is based on data collected by the author. The dataset includes product prices and categories that I obtained from Ukrainian online marketplace hotline.ua. SEO scores of online stores were estimated and gathered using Python script.

The research uses regression methods and quantitative analysis to test the main hypothesis:
Does firm scale influence product prices?

Finally, I discovered that firm scale indeed influences product prices, but the relationship is not linear. Larger firms usually have smaller price differences on average. However, the larger company is, the weaker the effect becomes.

CHAPTER 2. INDUSTRY OVERVIEW AND RELATED STUDIES

The e-commerce industry is growing fast around the world and uses economies of scale to reduce costs and increase profits. According to Statista (2025) in 2025, revenue in the e-commerce market will reach about US$2.88 billion. By 2030, the market volume is expected to be US$3.59 billion, with an annual growth rate (CAGR) of about 4.56%. Most revenue comes from the United States, where the market is worth US$1.17 trillion in 2025. The number of e-commerce users is estimated to reach 16.7 million by 2030. User penetration will be 42.5% in 2025 and 44.4% by 2030. The average revenue per user (ARPU) will be US$189.95.

2.1 Online marketplaces and price competition

Online marketplaces are websites where firms can publish their goods for sale and customers can compare prices from different firms. Choi and Mela (2019) investigated how online marketplaces make money. Authors state that marketplaces earn may earn from advertising fees (like CPM, CPC, CPA) and from commissions on sales. The study explains a trade-off between letting sellers pay to move products up in search and possibly making it harder for buyers to find relevant items with the same time. Evidently, moving advertised goods higher in search may reduce profit for sales, because less customers find what they need in minimum number of clicks and marketplace company may don't get its fee. However, it can make sellers pay more for possible better advertised position, which may bring in more advertising revenue.

Choi and Mela tested different rules for showing items. Their best result is using a Cost Per Click (CPC) auction for the top five positions, and sort items below fifth place by expected sales revenue. It raises profits by 181%, because it balances advertising fee income from top positions with transaction fees lower down , as Choi and Mela (2019) states.

They also find that simply ranking by consumer preference (like lowest price first) can hurt profits. Buyers then may find cheaper items early, that reduces commission for the platform (because it is usually percentage value). This can be important to understand that marketplaces are usually not interested in providing lowest price first for the customers but more likely looking for best balance for them and e-commerce stores, but not users.

Also, price competition can play an important role in e-commerce. Gerpott and Berends (2022) says that Bertrand competition model may explain how firms compete on price when they sell identical products with equal production costs. In this model companies set prices at the same time, and customers always buy from the firm with the lowest price. The theory shows that when all firms set price as production cost, it leads to the only stable outcome, where all companies earn zero profit. This happen because when any firm set price above cost, then any other firm more likely will charge lower price and capture the entire market demand.

However, this traditional model has a disadvantage. It assumes identical costs among competitors, which is not like in real world. In online retail firms often have different costs due to different expenses, marketing, operational efficiencies, etc. Large e-commerce companies with stronger marketing may achieve lower average costs per sale, so they are able to have prices below competitors while still being profitabile, creating a problem in standard Bertrand equilibrium prediction.

2.2 Company Size, SEO and Competitive Advantages

We know about economy of scale and about possible relationship between company size and competitive advantages. Economic theory says that larger firms often have lower costs and better profitability compared to smaller ones. This happens because big companies may use their size to get better deals, reduce expenses or just work more efficiently.

Nowadays, in our digital world, we can see similar situation in e-commerce businesses. Larger online retailers often can have cost advantages that let them offer lower prices to customers. One important point is advantages is digital marketing (SEO). When big e-commerce companies invest more in their marketing, they can attract customers at lower costs than smaller firms due to having more resources.

At the same time, Sharp and Dawes (2002) found an interesting rule of economy of scale in marketing of traditional markets. They showed that big brands may lose fewer customers each year compared to small brands. This means big companies have lower churn rates. They possibly keep their customers longer without spending extra money to replace them. For example, if there are 2 brands in the market and both brands gain and lose the same number of customers. But first company is lower and second one is larger. In this situation, the smaller brand more likely loses a much higher percentage of its total customer base compared to the big brand, because big one possibly has more clients.

Such situation creates so called "Double Jeopardy" smaller brands have fewer customers and lose them more often. It forces small companies to spend more money on getting new customers to replace the ones they lose.

I believe that the same logic can be applied to e-commerce markets today. Large online retailers with strong SEO more likely will attract customers through organic search results, which may cost much less than paid advertising. Small e-commerce firms usually have weaker SEO, so they may spend more money on paid ads to get the same number of customers. This can. create a cost advantage for bigger firms. When large e-commerce companies have lower customer acquisition costs due to possible better SEO, they may offer products at lower prices and making profit from it. This price advantage helps them compete better and grow even larger, creating a cycle where big firms become more successful.

At the same time, Ukrainian e-commerce market is still developing, what is interesting to study. I believe that some theories about economies of scale may work differently here because of different market conditions, consumers or other economic factors. Ukrainian online shoppers may be more price-sensitive and comparison-minded due to material situation or cultural aspect. So, it makes pricing strategies even more important for e-commerce success.

CHAPTER 3. METHODOLOGY

This work focuses on determining if the economy of scale pushes down the prices in e-commerce firms.

3.1 Approach

The methodology combines quantitative analysis and regression models. We compare company scale and website SEO score against product price to assess whether economies of scale and higher digital visibility impact pricing for consumers. For the reason we have cross-sectional data (one observation), we need to minimize influence of seasonal firm discounts. Hence, it was decided to follow the algorithm:

1) Choose **j** sets with **n** products that have intersection in **m** shops
2) Calculate mean price of **n** products
3) Calculate price difference between shop and mean prices in percent value for specific set of products.

This approach let us neglect shop discount and look at average price for the set of products, compare companies based on relative pricing rather than absolute prices that may differ due to different factors.

In general, there are different factors that can affect the price, for example, market power and monopolization that urge firm to take more surplus pushing price up. Price competition and economies of scale may push price down.

Therefore, we can express firm price for the good as:

$$P_i = y_i + f(employeeNumber, seoScore) + e_i \quad (1)$$

$$y_i - mean\ price\ of\ good\ i$$

However, so far, the data is cross-sectional it was decided to choose product combinations that share the same product list of firms. This makes the regression model more accurate and have more control on seasonal discount on specific goods.

Then, we can express price for the product combination as:

$$P_j = z_j + f(employeeNumber, seoScore) + e_i \quad (2)$$

where

$$z_j = \frac{1}{k}\sum_{i=1}^{k} y_i \text{ (mean price of product combination thorough shops)}$$

$$k = amount\ of\ products\ in\ combination$$

Hence, if we subtract mean price of product combination from both sides we get difference between shop and mean product combination prices:

$$P_{jDiff} = f(employeeNumber, seoScore) + e_i \quad (3)$$

My goal is to find if the compound price difference is generally lower in scaled firms, than smaller ones.

3.2 Data Collection Strategy

To do the research, there's need to build a dataset of companies with their marketing power, scale and prices:

In my research marketing performance is measured by website SEO score collected with python script using advertools library. SEO optimization taken as the most appropriate marketing approach for E-Commerce because:

- It directly affects how customers find products online
- It reflects long-term marketing investment rather than short-term advertising spending
- It shows how well a company understands digital marketing
- Sometimes it correlates with organic traffic, which reduces customer acquisition costs

Company scale is measured by number of employees. This number often is considered as proxy measure for company size. The employee number was gathered manually from firm vacancies. Companies where number of employees was not found were considered as small companies (less than 100 employees). In general, I classify 3 types of companies: small (0-100 employees), medium (101-999 employees), large (1000+ employees).

Prices were collected using the Hotline.ua marketplace during single observation in August 2025, so it includes some seasonal firm discounts. Hotline.ua was chosen because it is one of the largest price comparison platforms in Ukraine, where many e-commerce stores list their products.

Companies and their products were chosen by author without any specific factor to ensure representativeness across different product categories and company sizes.

3.3 Empirical Model

Now let's use regression analysis to test the main hypothesis. Previously we determined formula for percent price difference for combination of products as

$$P_{jDiff} = f(employeeNumber, seoScore) + e_i \tag{4}$$

Number of employees can be used as company scale that pushes down the price, but different company size may impact price differently. Therefore, relationship between firm size and pricing may be non-linear and we should use quadratic term. Moreover, we should use log to squash employee variability. To avoid multicollinearity of employee number and (employee number) ^{2} we will use centered employee number:

$$centeredEmployee = employeeNumber - \ mean(employeeNumbers) \tag{5}$$

Also, to control effect of different product categories (beauty, smartphones, sport, etc) we should add category dummies.

I estimate the following model equation:

$$\begin{aligned} priceDifferencePerecent \\ &= const + \beta_1 seoScore + \beta_2 \log(centeredEmployee) \\ &+ \beta_3 [\log(employeeNumber)]^2 + \cdots categoryDummies + u \end{aligned} \tag{6}$$

Dependent variable is price difference in percent (percent deviation from market average price for the same products)

Independent variables are:

- SEO Score: Numerical score representing website optimization quality
- log (Employee Number): Natural logarithm of company employee count

- [log (Employee Number)]^2: Squared term of the natural logarithm of company employee count
- …categoryDummies: Dummy variables for all product categories to control for their effect.

If economies of scale work, the expected result is negative coefficient for employee number (larger companies have lower prices).

3.4 Limitations

This research has several limitations that should be considered:

- Cross-sectional data limits our ability to see trends over time, therefore some global Ukrainian trend may impact whole model because we capture only temporary market conditions.
- Companies do not share exact number of their employees. We can only find approximate and rounded up data. I.e. 500+employees, 10-50 employees, etc. Hence, if many firms are placed only in broad ranges, we may lose real price variation between larger and smaller companies.
- SEO score calculation I used is only one of many possible implementations for SEO score calculations. Therefore, some other approaches may give other numbers.
- Seasonal effects and promotional campaigns still might affect price comparisons

To sum up, this research examines how firm size and SEO optimization affect the final prices offered to consumers in Ukrainian e-commerce. The data is drawn from a broad cross-section of online stores and products listed on Hotline.ua, allowing for statistical testing of how structural and digital factors shape consumer outcomes.

CHAPTER 4. DATA

The data was collected during a single observation period in August 2025. The data include more than 100 firms split by different types, depending on number of employees. SEO scores were collected using advertools library in python. The dataset consists of various product categories: LEGO, Energy Supply, Computers, Networks, Beauty and Health, Household Appliances, Smartphones, Smartwatches, Sports, Active Recreation, TV, Audio, Video, Photo and their subcategories.

Table 1. Descriptive statistics.

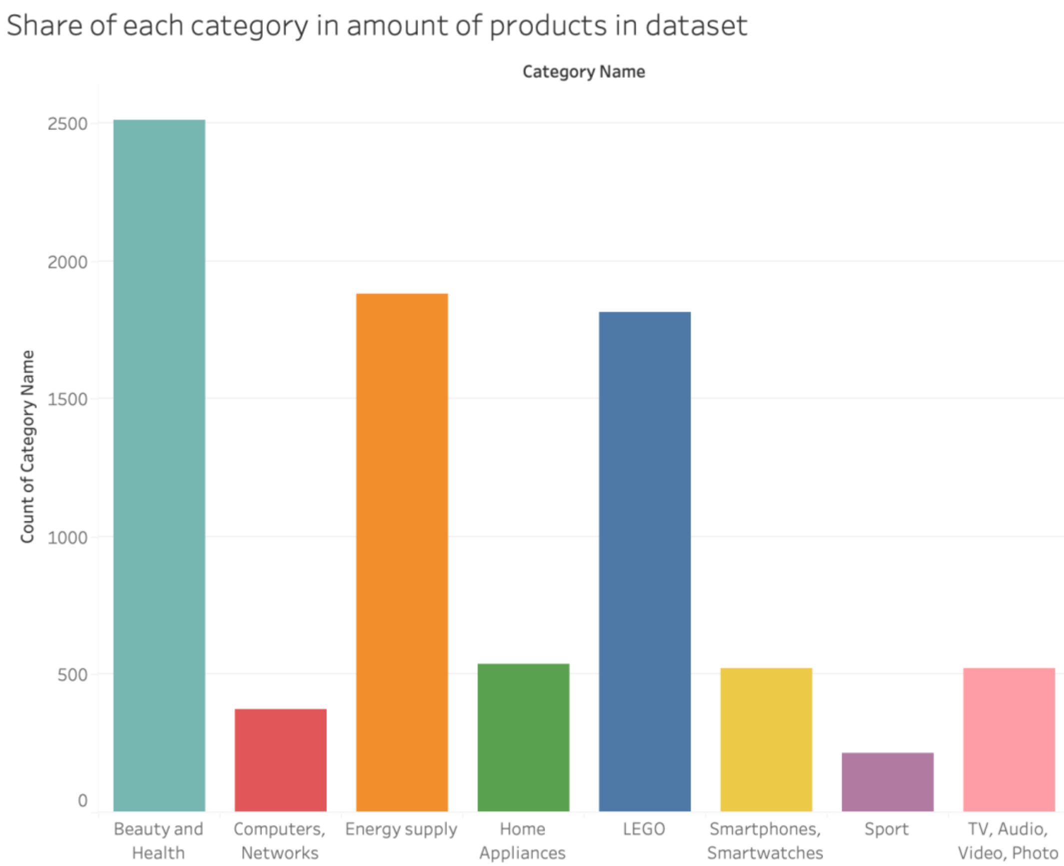
	SEO score	Employee Count
count	11282	11282
mean	70.90	2762.31
std	6.38	8506.25
min	52	10
25%	67	50
50%	67	250
75%	74	1000
max	86	38000

Source: composed by the author.

4.1 Product Categories Distribution

On Figure 1 we can see the distribution of products across different categories in our data sample. The product selection apparently covers a good range of consumer goods. Such variation helps us to be sure that our results are not specific to specific product, but I believe that results will reflect general patterns in e-commerce pricing. In our data electronics and computer products make up take a big pie due to specific process of data gathering. Also, I believe that having high-tech products (smartphones or computers) and everyday items (household appliances, beauty products) allows us to see if company size effect can work differently across different product types. Some categories might be more price-sensitive, and some companies might have different advantages depending on the product category or else.

Figure 1. Products distribution in the sample categories.



Source: composed by the author.

4.2 Company Size and Employee Distribution

Figure 2 below demonstrates the distribution of companies by size categories: small, medium, and large. Here we can clearly see that most stores in our dataset are just small businesses, when medium and large firms take almost quarter of the market firms quantity share. It looks realistic, because in the real world we can really see such picture of e-commerce. This distribution matches what we expect in from economic theory as well - many small companies and fewer large ones. What about classification. I divided companies based on number of employees:

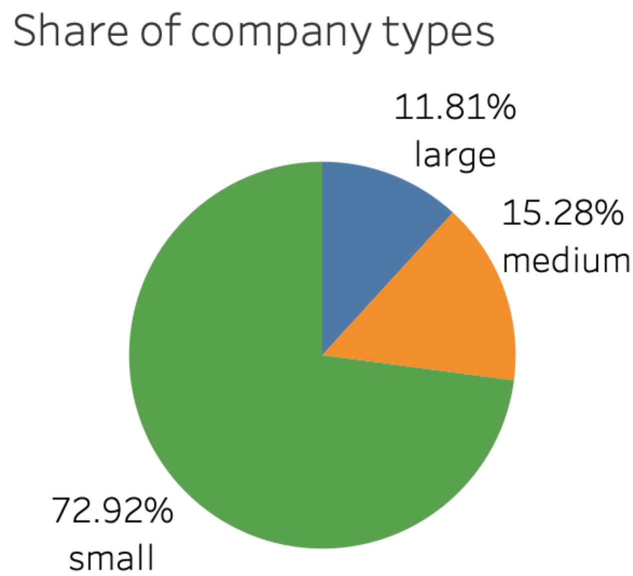
- Small companies (under 50 employees). They are typical small e-commerce businesses.

- Medium companies (50-999 employees). They are growing businesses that have some scale but are not yet dominant

- Large companies (1000+ employees): They are established players with significant market presence

This distribution is good for our analysis because it may reflect the real structure of the Ukrainian e-commerce market (at least I believe so). However, the big amount of small companies means we need to be careful about their statistical power when comparing groups of products.

Figure 2. Company types distribution in the sample: small, medium, large.

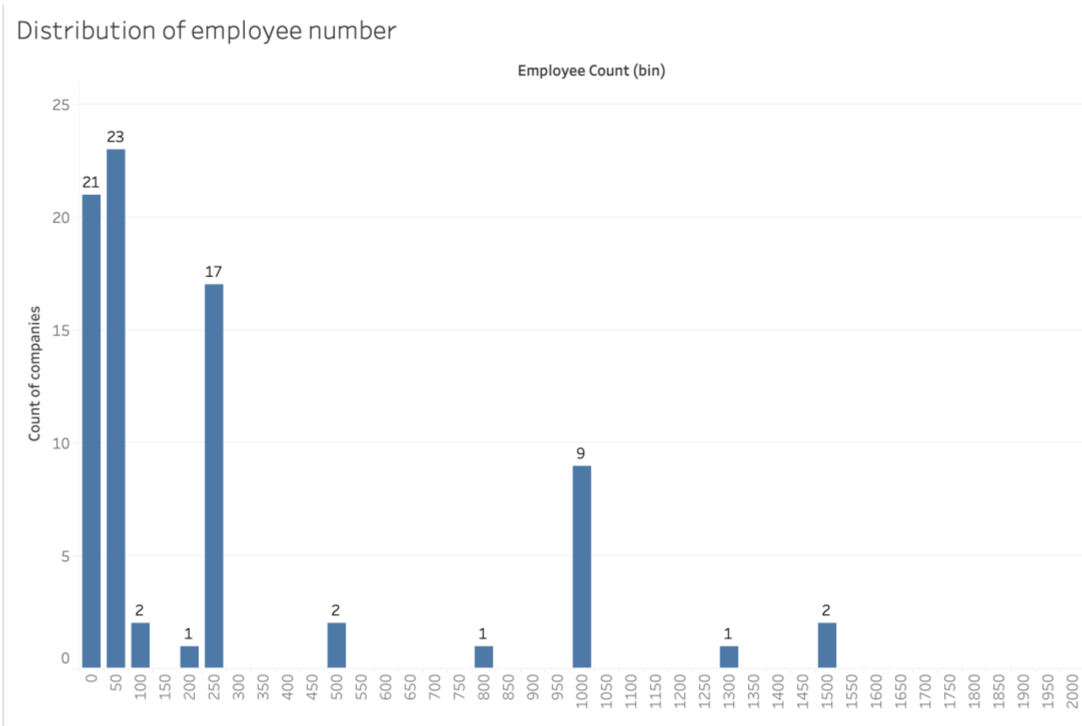


Source: composed by the author.

Figure 3 shows the detailed distribution of employee numbers across all companies in the sample. Nevertheless, such employee distribution requires data transformation. The distribution is highly skewed, with most companies having very few employees and only a small number having many employees. This is why we use logarithmic transformation of employee numbers in our regression model - it helps make the relationship more linear and reduces the influence of extreme values.

The long tail in this distribution is typical for business size data. A few very large companies employ hundreds of people, while most companies are small operations with just a few dozen employees. This pattern is common in developing e-commerce markets where the industry is still consolidating.

Figure 3. Distribution of companies by number of employees.



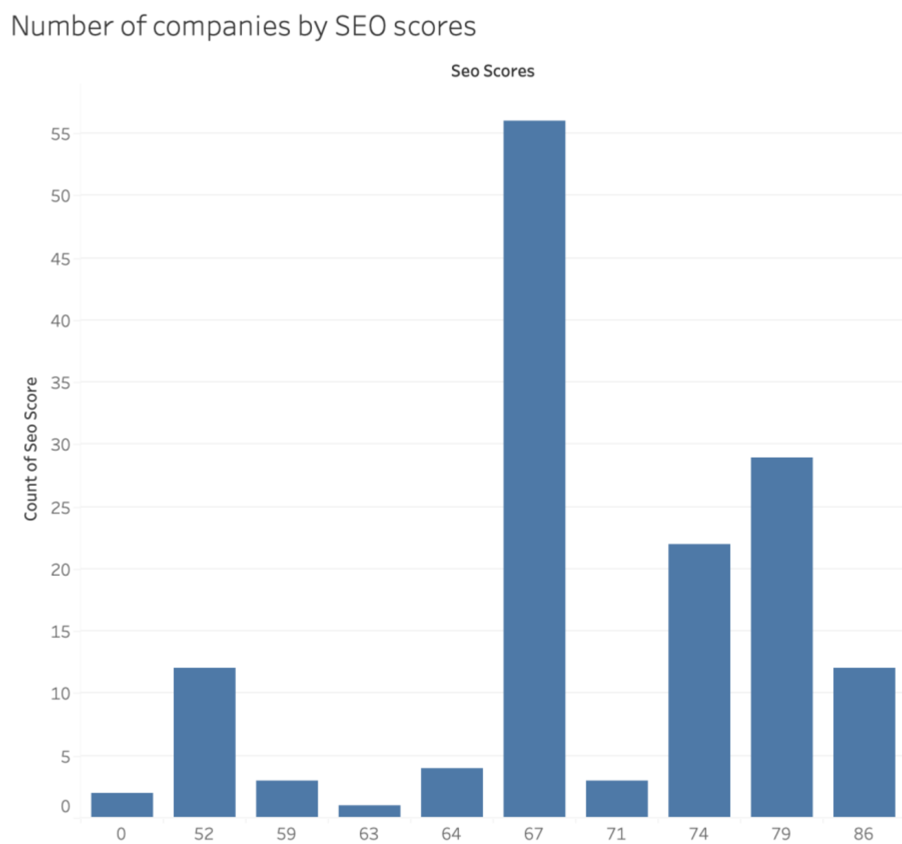
Source: composed by the author.

4.3 SEO Score Distribution

Figure 4 presents the distribution of SEO scores across all companies in the sample. This distribution suggests that e-commerce companies in Ukraine generally do not invest much into SEO (the highest bar on 67) , but still we have great share of scores in the range of 74-86. However, we cannot see any website that achieves 100 mark, it means either: SEO score calculation approach can be better or there are just no websites in dataset that achieved best Search Engine Optimization.

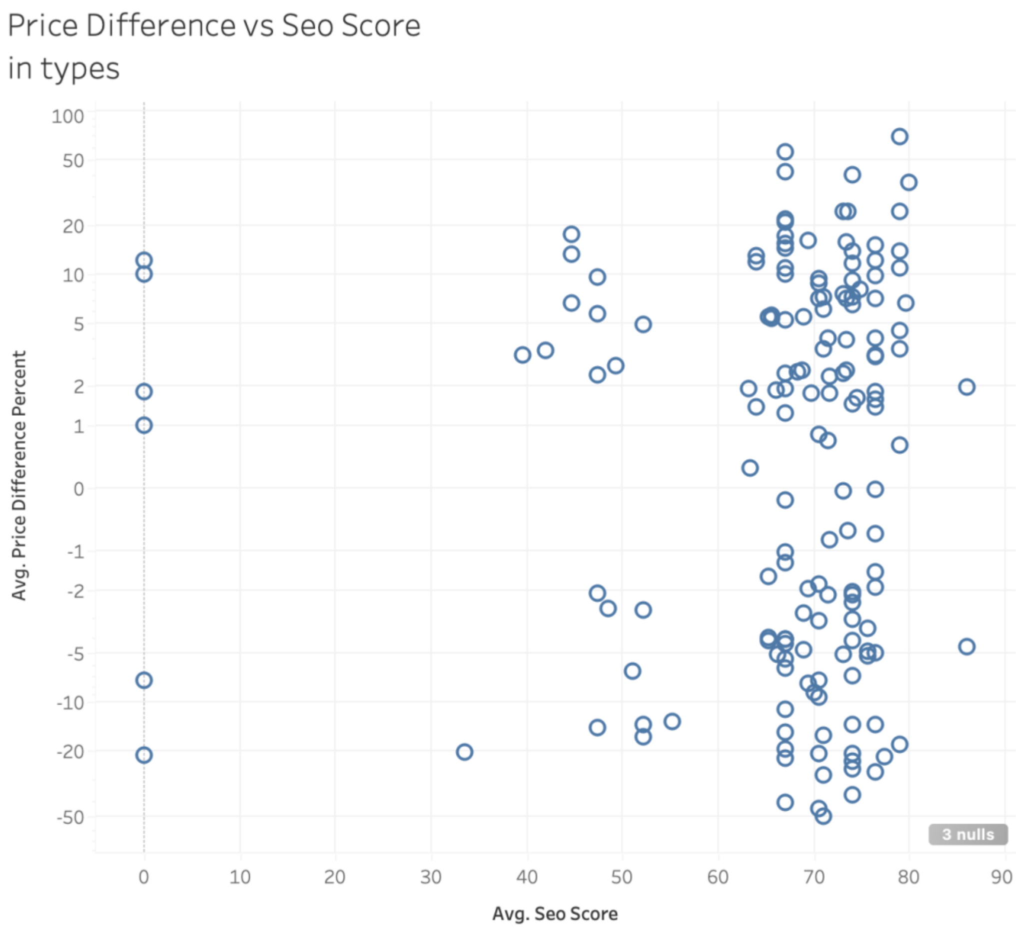
Figure 5 shows relationship between price difference and SEO score. Apparently, the distribution of SEO scores is nonlinear so we cannot assume linearity for our OLS model. Also, after logarithmic, square and mean transformation tries – nothing helped, so it was decided to leave scores as they are.

Figure 4. SEO score distribution in the sample.



Source: composed by the author.

Figure 5. Map of price difference vs SEO score.



Source: composed by the author.

Data Quality Notes:

- All price data was collected on the same day to avoid temporal price changes
- SEO scores were calculated using one of possible approaches. So, the scores are consistent between each other but possibly calculated not in the best way. Also, we cannot assume linearity for SEO Scores.

- Employee data was verified from multiple sources where possible
- Missing employee data was handled by assigning companies to the "small" category

The dataset provides a good snapshot of the Ukrainian e-commerce landscape in August 2025, with sufficient variation in company sizes and SEO performance to test our hypotheses about economies of scale and pricing strategies.

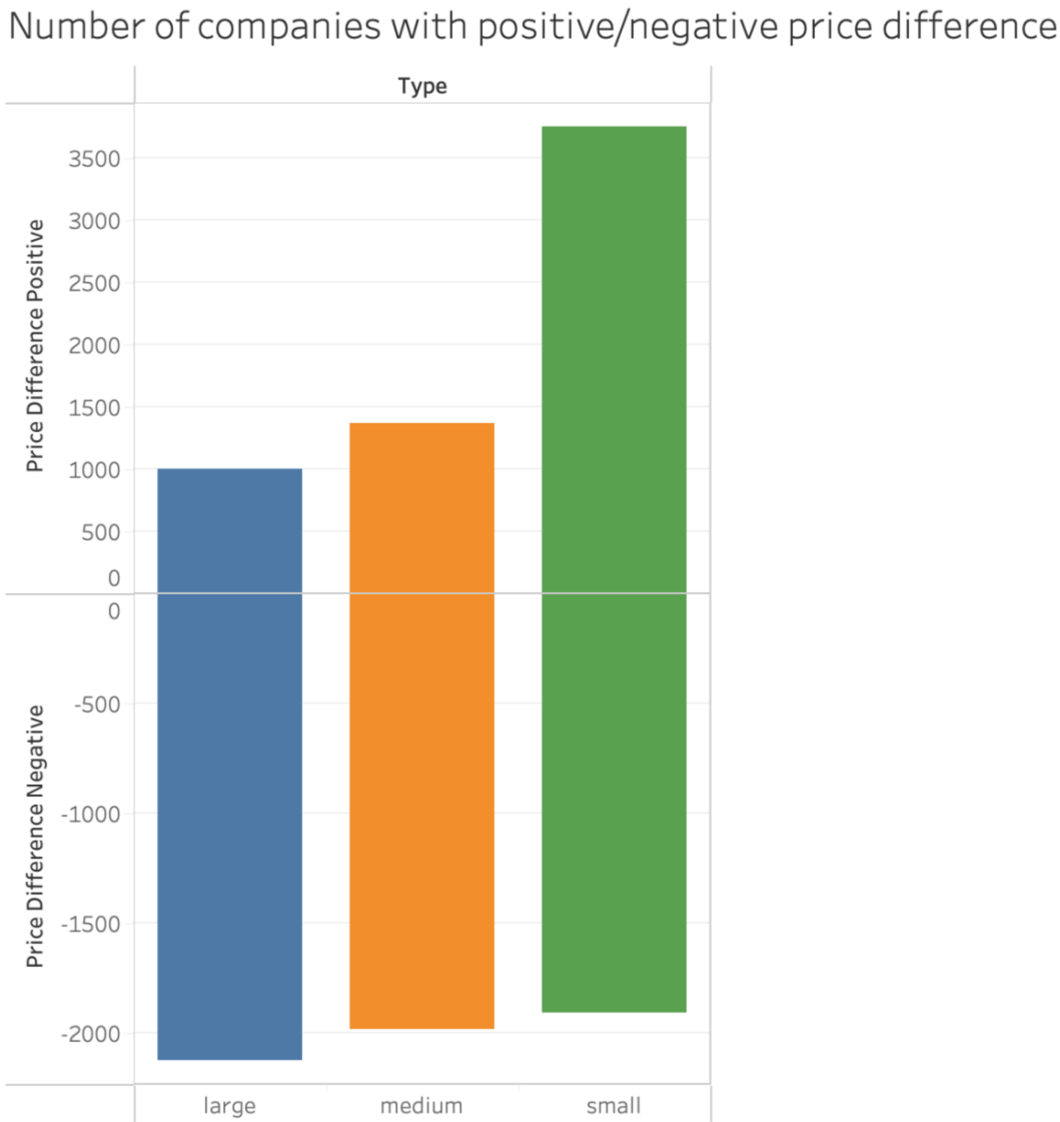
CHAPTER 5. RESULTS

5.1. Preliminary analysis

Figure 6 shows the distribution of positive and negative price deviations across different company types. We can easily see that small companies tend to have positive price deviation among other company types. This may support our main hypothesis about economies of scale. When small companies have positive price deviations, it means they more likely charge higher prices compared to the market average for the same products.

The pattern not that clear and firstly pricings is hard to attach to company sizes. However, we can see that small companies tend to have positive price deviation and charge above average market price. Medium companies have some mixed results and more likely charge less than average market price, but in general not that often. So, large companies more likely will have negative price deviation (charge below average). This suggests that larger companies probably do pass some of their cost advantages to consumers through lower prices, making them better off. However, the relationship is not perfect. We can see small companies with competitive prices and large companies with premium pricing.

Figure 6. Positive/negative price difference for company types.



Source: composed by the author.

We see that Figure 7 presents a scatter plot showing the relationship between SEO scores and price deviations, with different colors representing company sizes. The medium sized companies tend to have lower SEO scores than small and large do. Probably, this's the reason why they are good, but not great.

The scatter plot reveals several interesting patterns:

- Large companies (blue dots) tend to spread across different SEO scores but are more likely to have negative price differences

- Medium companies (orange dots) dots tend to spread at lower SEO scores with mixed price performance

- Small companies (green dots) tend to spread across different SEO scores but more likely to have positive price deviations

So, from the visualization we can see that SEO performance alone doesn't determine pricing. Large companies may offer competitive prices even having moderate SEO scores, possibly because their economies of scale neglect for less efficient digital marketing. Small companies with good SEO might still charge premium prices, maybe because they target niche markets or offer specialized services.

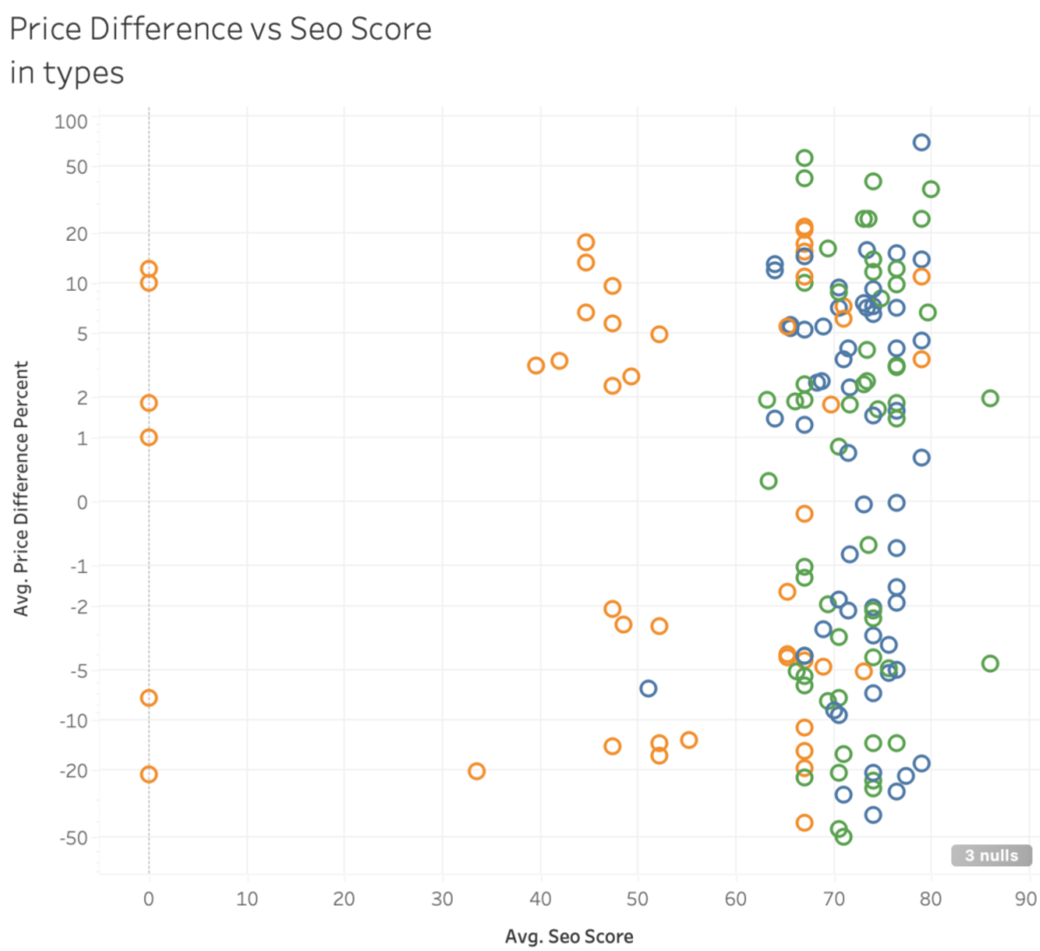
The medium-sized companies present an interesting case - they seem to underinvest in SEO compared to both small and large competitors. This might explain why they struggle to achieve the cost advantages of large companies or the flexibility of small ones.

Figure 7. Price Difference vs SEO Score.

Blue – large

Orange – medium

Green – small



Source: composed by the author.

5.2. Regression Model Results

On the Table 2 we can see regression results, where the dependent variable is the price difference in percent. The models include product number of employees, and SEO score as factors. Also, second model has control for categories to determine if there are category impact on price.

Table 2. Regression models result.

	Dependent variable: price_difference_percent	
	Base	Category
	(1)	(2)
category_Energy Supply		-2.972***
		(0.909)
category_Computers, Networks		-1.480
		(1.246)
category_Beauty and Health		-2.454**
		(1.077)
category_Home Appliances		-2.247*
		(1.227)
category_Smartphones, Smartwatches		-3.484**
		(1.402)
category_TV, Audio, Video, Photo		-3.712***
		(1.333)
const	-12.083***	-9.896***
	(2.617)	(2.692)
log_employee_count_centered	-7.178***	-7.199***
	(0.166)	(0.166)
log_employee_count_squared	0.526***	0.524***
	(0.042)	(0.042)
seo_score	0.211***	0.211***
	(0.037)	(0.037)
Observations	11282	11282
R^2	0.147	0.148
Adjusted R^2	0.147	0.148
Residual Std. Error	33.251 (df=11278)	33.237 (df=11272)
F Statistic	802.984*** (df=3; 11278)	273.770*** (df=9; 11272)
Note:		*p<0.1; **p<0.05; ***p<0.01

Source: composed by the author.

Employee Number Effect (Economies of Scale): The coefficient of -7.178 for log_employee count and 0.526 log_employee_count_squared are highly significant. These numbers mean that when firm size grows, price difference becomes smaller at first. However, after some point, the effect changes direction: very large firms may again increase the price. The reason may be increased operational costs or higher market power.

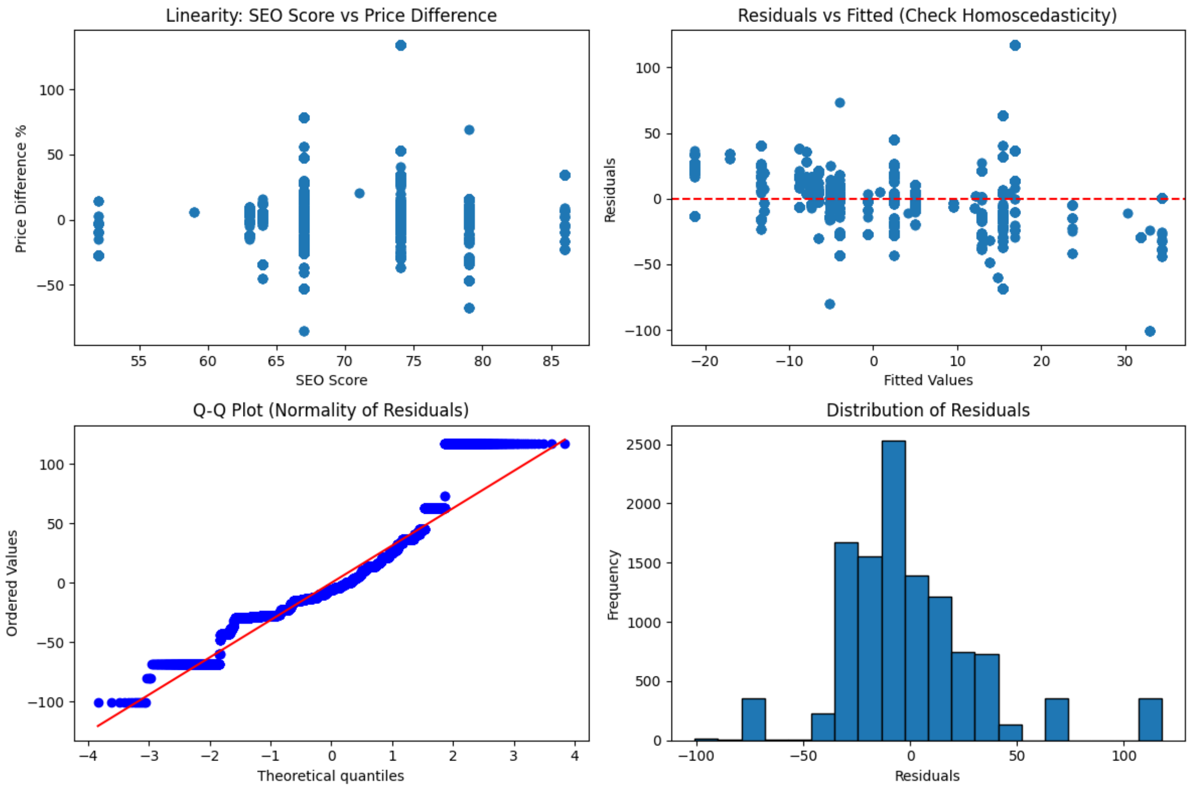
SEO Score Effect: The coefficient of 0.211 for SEO score is also highly significant. So, for every 1 unit increase in the SEO Score, the price deviation from mean price is expected to increase by nearly 0.2%. This means that companies with better SEO tend to charge slightly higher price. For example, if the mean price among several shops for the combination of products is 500 UAH then, in specific shop 1 more unit of SEO score will increase the mean price on 1 UAH.

The R-squared value of 14.7% indicates that our model explains about 14% of the variation in price differences. While this might seem low, it's reasonable for cross-sectional pricing data where many factors influence prices.

Figure 8 shows the results of assumption tests for OLS model. The residual plot shows that the variance of errors changes with SEO score levels, which violates one of the key assumptions (heteroscedasticity). This heteroscedasticity means our standard errors might be biased, so the significance levels are not that trustworthy.

The non-linear relationship between SEO and prices flows out from data quality. So, in our case relationship between SEO score and pricing might be more complex than our simple linear model captures.

Figure 8. Assumption tests for OLS.



Source: composed by the author.

However, after results analysis it was assumed that SEO score estimation may be not correct due to opposite nature of companies with positive and negative price differences. There were built few more regression models that express the same dependent and independent variables, but with two datasets: first with positive price differences, second with negative price differences. This way we can estimate SEO score coefficient considering possible opposite nature of companies with different price differences.

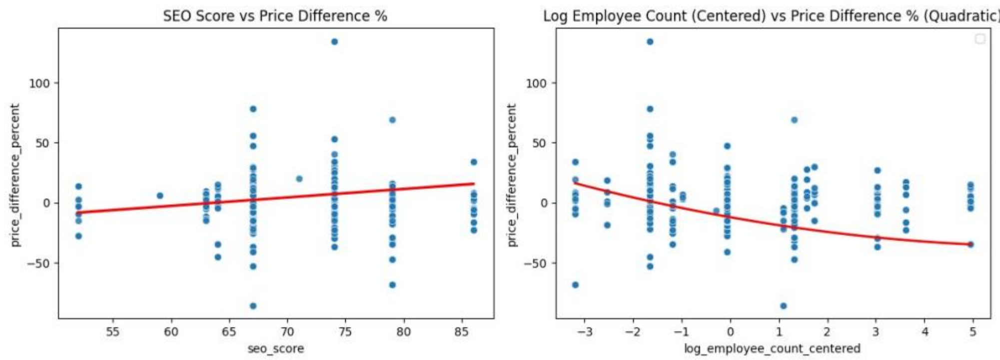
On the Table 5.2.2 we see that the SEO score coefficient becomes weaker and mostly insignificant once the sample is divided. In our case pooling all firms together leads to overestimates of the SEO score effect. So, we can assume that SEO score does not have and meaningful impact on price difference.

Also, we can see changes in employee count effect, what is completely logical after data split what disorders quadratic relationship.

Table 3. Regression models result after data split.

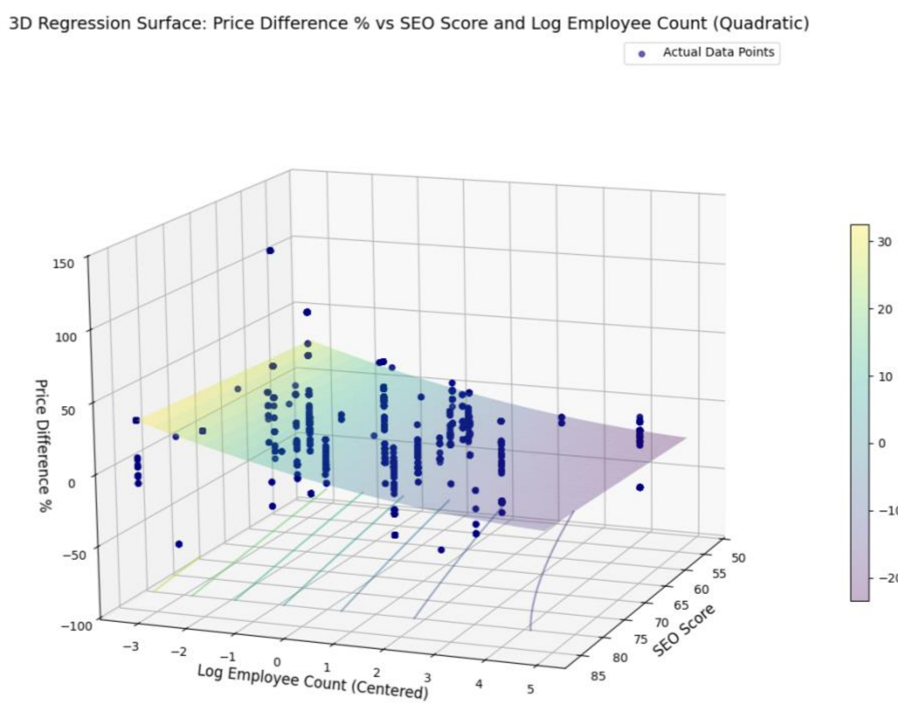
	Dependent variable: price_difference_percent			
	Positive Price Diff	Positive Price Diff Category	Negative Price Diff	Negative Price Diff Category
	(1)	(2)	(3)	(4)
category_Energy Supply		-4.529***		3.389***
		(1.226)		(0.540)
category_Computers, Networks		-9.016***		5.479***
		(1.708)		(0.774)
category_Beauty and Health		-6.253***		5.029***
		(1.479)		(0.675)
category_Home Appliances		-5.958***		4.295***
		(1.693)		(0.739)
category_Smartphones, Smartwatches		-2.279		2.987***
		(2.072)		(0.765)
category_TV, Audio, Video, Photo		-6.091***		2.498***
		(1.802)		(0.817)
const	23.152***	24.391***	-16.850***	-20.966***
	(3.924)	(3.924)	(1.919)	(1.925)
log_employee_count_centered	-4.515***	-4.362***	0.068	0.139
	(0.198)	(0.199)	(0.182)	(0.182)
log_employee_count_squared	-0.544***	-0.597***	-0.721***	-0.732***
	(0.057)	(0.058)	(0.045)	(0.045)
seo_score	0.091	0.138**	0.008	0.022
	(0.057)	(0.058)	(0.027)	(0.027)
Observations	5528	5528	5754	5754
R^2	0.090	0.096	0.085	0.099
Adjusted R^2	0.090	0.095	0.085	0.098
Residual Std. Error	32.953 (df=5524)	32.865 (df=5518)	13.979 (df=5750)	13.881 (df=5744)
F Statistic	440.972*** (df= 3; 5524)	150.696*** (df= 9; 5518)	390.665*** (df= 3; 5750)	153.991*** (df= 9; 5744)
Note:				*p<0.1; **p<0.05; ***p<0.01

Figure 9. Linear and quadratic effects on price difference.



Source: composed by the author.

Figure 10. 3D regression surface for price difference.



Source: composed by the author.

5.3. Sum up

The preliminary analysis reveals that small companies have much higher probability of having higher price difference among shops, that means that prices in small shops also tend to be higher. Regarding medium and large sized firms – there is no evident conclusions about them that can be seen.

Also, it was found that middle sized companies tend to have much lower SEO scores due to different factors.

However, if we can look at regression result, we can clearly see quadratic relationship between employee number and price difference. It reveals that price difference is higher in smaller companies, then price difference decreases until when employee number increases until specific point and then start increasing again. Therefore, we can say that middle sized companies should have the lowest prices on the market (in our dataset middle sized companies have 101-999 employees).

Moreover, I examined the same regression models with split data on negative and positive price difference to study SEO score coefficient better. It was found out that with split data SEO score coefficient is not meaningful and can be completely neglected, even though the coefficient is statistically highly significant.

The results provide evidence that economies of scale in e-commerce markets do benefit consumers until large size. Hence, corresponding policies that allow companies to grow are helpful, but they should maintain competitive market structures.

CHAPTER 6. CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

This research studied how company size and digital marketing capabilities (SEO scores) affect pricing in Ukrainian e-commerce markets. There were analyzed over 100 companies in Hotline.ua, their SEO scores, products with pricing strategies they use.

The most important discovery is that company size is the main reason why prices differ. This can be explained by the theory of economies of scale. As theory says, small companies usually charge higher prices, which makes sense, because they don't have the cost benefits of buying or producing in huge amounts or having big production scale. On the other hand, we believe that large companies usually offer lower prices (because they probably will share cost savings with customers). However, the data and analysis show that this price drop slows down for the very biggest companies, and their prices might even start to go up again for big companies.

I also looked at the SEO score, which is a probable measure of a company's digital marketing success (assumed in my research). First look at the data hinted that good SEO meant slightly higher prices due to higher costs, but my idea was wrong, when we investigated the numbers more closely. After separating the companies on high pricing and low pricing, we found that SEO performance has little to no real impact on pricing decisions.

Interestingly, medium-sized companies look to be falling behind. They have the lowest SEO scores of all the groups. They might be struggling because they can't match the low costs of large firms or probably cannot match the unique appeal of small firms.

6.2 Recommendations

Company size is the dominant factor in pricing, as we understood from the research. Firms should act considering their size. Small companies cannot win on cost, so they create a premium value proposition. It means they should invest in special expertise, or user experience to show off, or highly unique products to explain their high prices. However, trying to win in cost or price battle – is losing strategy, because bigger firms have an advantage in this.

For medium-sized companies I can recommend trying to close the competition gap with large companies and gap in digital presence. I believe that they invest in their digital marketing and SEO to increase visibility to attract more customers. Simultaneously, they shouldn't forget about keeping costs low to be competitive in probable price race with other middle-sized companies.

My recommendation for large companies is trying to focus on optimization of their processes to keep prices low, not only looking into their scale. Even though scale allows them to offer lower prices, they should monitor increases in operational complexity or costs, which may increase prices again. They should use their size advantage, but be sure that their massive size doesn't lead to probable inefficiency.

For policymakers the recommendation is straightforward – let companies grow, but not too much. This way, we can achieve maximal welfare of consumers.

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