



Communication

An Experimental Pricing Framework for E-Commerce

Puneet Vatsa ¹, Wanglin Ma ¹ and Xiaoshi Zhou ^{2,3,*}

- ¹ Department of Global Value Chains and Trade, Faculty of Agribusiness and Commerce, Lincoln University, Christchurch 85084, New Zealand; Puneet.Vatsa@lincoln.ac.nz (P.V.); Wanglin.Ma@lincoln.ac.nz (W.M.)
² National School of Development, Peking University, Beijing 100871, China
³ School of Economics and Management, Nanjing University of Science and Technology, Nanjing 210094, China
* Correspondence: Xiaoshi.Zhou@outlook.com

Abstract: Characterizing the demand curve of products is important for pricing them optimally. However, in deriving empirical demand curves, econometricians have to contend with identification issues. Furthermore, theoretical demand curves derived using standard economic theory are divorced from empirical realities: firms rarely have information on customers' budget constraints; theoretical utility functions are seldom derived empirically. Recognizing these issues, we propose an experimental approach for determining a product's demand curve and, in turn, its profit-maximizing price in online environments. The proposed approach yields precise estimates and is quick and inexpensive to implement.

Keywords: pricing strategy; profit maximization; digital products; experimental analysis



Citation: Vatsa, P.; Ma, W.; Zhou, X. An Experimental Pricing Framework for E-Commerce. *J. Theor. Appl. Electron. Commer. Res.* **2021**, *16*, 2571–2578. <https://doi.org/10.3390/jtaer16070141>

Academic Editor: Eduardo Álvarez-Miranda

Received: 6 August 2021
Accepted: 22 September 2021
Published: 28 September 2021

Publisher's Note: MDPI stays neutral with regard to jurisdictional claims in published maps and institutional affiliations.



Copyright: © 2021 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

E-commerce offers firms opportunities to price their goods and services dynamically using data-driven approaches [1–6]. Nevertheless, achieving the correct price can be complex, as firms continually grapple with understanding consumer perceptions, ascertaining their competitive position, and enhancing their value propositions. This paper proposes an easy-to-implement intuitive experimental framework for deriving empirical demand schedules to inform pricing decisions. We contend that this framework is widely applicable in the context of digital commerce and does not suffer from the drawbacks of econometric methods and standard economic theory. Furthermore, the framework is well-suited to a test-and-learn environment, rapid deployment, and customer-centricity, which are hallmarks of successful E-commerce operations. For illustrative purposes, we consider the example of the digital games industry that comprises many firms but only a few dominant ones. However, the discussion can be generalized to firms selling goods and services online and those that monetize other scalable digital products and services such as video streaming, social media platforms, online learning delivery systems, and business analytics software. To date, with the exception of Castronova et al. [7], who experimentally estimated the demand elasticity of digital items in an online game and reported that the price elasticity of the demand was -0.431 , research in this field remains scarce.

The demand for digital products is soaring [8–10]. The COVID-19 pandemic has accelerated the digitization of global commerce, and this trend is likely to continue. Digital games, for instance, are projected to grow secularly over the coming years as more and more people worldwide gain access to the internet and modern information and communication technologies (ICTs) such as smartphones, computers, and tablets [11–16]. Furthermore, the costs of producing and launching these products, owing to rapid advances in technology, continue to decrease. Nowadays, developing ICT-based applications is relatively inexpensive. Thus, it stands to reason that more and more publishers are entering the industry, creating an abundance of digital products; one can confirm this with only a cursory search on the App Store or Google Play. However, only a few products are thriving and many fail to break even, with some earning only a few dollars. Why is this the case?

Curating high-quality digital products and services can entail considerable outlays. Behind successful products are teams comprising software developers, product designers, producers, artists, data scientists, database administrators, marketers, accountants, and office administrators. Costs associated with salaries, rent, office supplies, and hardware can be significant. Because entry barriers are low, many firms enter these endeavours; however, because the operating costs are high and the competition is stiff, very few endure. As a result, only a small number of firms earn a large proportion of their revenue in this industry [17].

The few dominant firms in the industry compete amongst themselves for market share while striving to maximize profits. On the one hand, they may consider raising prices to increase revenues; however, the prospect of increased customer churn serves as a deterrent; would an increase in prices dissatisfy customers and cause them to unsubscribe? Would higher prices prevent potential customers from subscribing? To alleviate these concerns and increase their customer base, firms may lower prices or intermittently offer discounts to maintain or increase the number of customers [18,19]. However, this strategy will undoubtedly reduce the average revenue per customer; whether the customer base grows sufficiently to yield a higher total revenue will remain to be seen. Herein lies an important dilemma: Should the firms increase prices, decrease prices, or leave them unchanged? Alternatively, how elastic is the demand for the product? The answer lies in estimating the demand curve.

2. Methodological Framework

2.1. Deriving an Empirical Demand Curve

Analysts seeking to estimate a demand curve empirically often contend with the identification problem. Since observed prices arise from the interaction between the ever-changing supply and demand forces [20–22], merely joining various pairs of prices and quantities, which in essence represent different equilibria, does not correctly identify the demand or the supply curve. However, if factors (such as customers' income, preferences, and the availability and prices of substitutes) shifting the demand curve can be controlled, then any changes in demand can be attributed to price changes; these changes will occur along the same demand curve. Be that as it may, in practice, controlling for different factors is onerous, as firms operate in continuously changing environments. Moreover, because the prices of many products change infrequently, there is seldom enough variation in historical prices. This makes the task of determining the effects of price changes challenging, if not impossible. In the presence of two or three price points, linear regression lines belie the true sensitivity of demand to different prices; also, they do not accurately represent non-linear demand curves.

Nevertheless, because game publishers operate in the digital space (which lends itself well to scaling, monitoring, and testing), they may derive the demand curve of their products inexpensively, quickly, and experimentally. Experiments and randomized control trials offer actionable insights specific to the context in which they are implemented. Unsurprisingly, they are gaining popularity amongst economists and policymakers [23].

Next, we discuss a concrete example to illustrate the experimental approach; in essence, this is a randomized control trial. Consider Firm A, which sells monthly subscriptions to a digital game, g , costing USD 5 via its website. The firm's competitors sell somewhat differentiated products at prices ranging from USD 4 to USD 10 per month. Firm A's management is not convinced that USD 5 per month is a profit-maximizing price. Furthermore, there is no consensus regarding the optimal price of g . Some managers believe that a lower price would entail higher profits; they believe that the demand for g is price-elastic and that a small reduction in the prices would induce customers to choose g over other alternatives. Others argue that raising prices would increase Firm A's profits. They assert that g 's demand is price-inelastic, the product is sufficiently differentiated, and its value proposition warrants a higher price. After debating the matter vigorously, they reach

an impasse and decide to settle the matter experimentally: let the customers speak for themselves.

Given that subscriptions are sold on the website, the web developers are tasked with creating four different versions of the membership webpage, and each version presents the customers with a different price point—USD 4, USD 5, USD 6, and USD 7. The versions are identical in every other regard. Thus, there is one control group (i.e., the customers exposed to the USD 5 version) and three experimental groups (i.e., customers exposed to the other price-point variations). Players may access some content without paying a subscription fee. In essence, this is the so-called freemium revenue model, which allows players to access selected features for free but requires them to pay for accessing the full array of functionality, which allows for a richer experience.

Furthermore, measures are taken to mitigate the likelihood of offering different price points to the same player; this is achieved by tracking web cookies. While geographically segmenting the customers may also accomplish this objective, this may necessitate adjustments to account for geographical influences for precisely measuring the effect of prices. The sample size for the experiment, which is directly related to the experiment’s duration, is determined based on historical information on conversion rates, the number of unique visitors to the website, and the desired levels of the margin of error and statistical significance. As such, the sample size is determined as follows:

$$n = \frac{N \times \hat{\rho} \times (1 - \hat{\rho})}{(N - 1) \times \frac{m^2}{z_{\alpha/2}^2} + \hat{\rho} \times (1 - \hat{\rho})} \tag{1}$$

where n refers to the sample size; N is the population size or the size of the addressable market; $\hat{\rho}$ is the historical conversion rate, which can be calculated by dividing the number of subscribers by the number of unique visitors per unit of time; m is the margin of error; and z is the z -value associated with the level of significance α .

The outcome of the experiment is binary: either players subscribe or they do not. Furthermore, the sample is large; the assignment of the players to the different versions of the subscription webpage is random, and the sample of visitors to the website during the experiment represents the population of interest. Thus, one may deduce from the experiment that the 95% confidence interval for the difference, $\hat{\rho}_i - \hat{\rho}_j$, between any two of the $n * \left[\frac{n-1}{2} \right]$ conversion rates, where $n - 1$ is the number of treatment groups, is $(\hat{\rho}_i - \hat{\rho}_j) \pm 1.96 * \left(\sqrt{\frac{\hat{\rho}_i \times (1 - \hat{\rho}_i)}{n_i} + \frac{\hat{\rho}_j \times (1 - \hat{\rho}_j)}{n_j}} \right)$.

Once sufficient data are collected, conversion rates for each of the four price points are compared; conversion rates can be tracked readily using web analytics software such as Adobe Analytics and Google Analytics. The price-point–conversion-rate pairs are plotted and analyzed. Connecting these points yields the empirical demand schedule. It bears emphasis that this schedule is unlikely to be linear or smooth. Furthermore, it may not even be monotonic. Since this schedule is derived from only a few discrete points, it is likely to be kinked, which renders it non-differentiable at inflection points. In this case, deriving revenue-maximizing price points using standard first-order conditions is not feasible. There is, however, a straightforward solution.

By multiplying the conversion rates by their respective price points and the expected number of visitors to the website, one can determine the price point associated with the maximum expected total revenue. This revenue-maximizing price point can be rolled out as digital game g ’s new price point. Of course, if the existing price point of \$5 yields the highest revenue, the status quo pricing is maintained.

2.2. Illustrative Example

For illustrative purposes, in Table 1, we present hypothetical data for the conversion rates, the number of visitors to the website during a period, and the subscriber’s lifetime

revenue. The latter assumes a lifetime subscription duration of six periods. Fifty thousand website visitors are randomly assigned to each of the four price groups. For each group, the conversion rate is multiplied by the expected number of total visitors to the website during a period. This yields the number of expected subscribers and multiplying this by the corresponding price level provides the expected subscription revenue from a full-scale rollout of specific prices. The data show that the conversion rate decreases as the price increases; however, the highest revenue is associated with the highest price. As the price increases from USD 6 to USD 7, a 16.67% increase, the conversion rate decreases by 2.44%, from 0.82% to 0.80%. Expectedly, the revenue increases. The empirical demand schedule and the expected subscription revenue associated with the different price points are plotted in Figure 1.

Table 1. Price, conversion, and total revenue.

Price	Subscribers	Samples of Visitors	Conversion Rate	Expected Total Visitors	Subscription Revenue
\$4	500	50,000	1.00%	1,000,000	\$240,000
\$5	470	50,000	0.94%	1,000,000	\$282,000
\$6	410	50,000	0.82%	1,000,000	\$295,200
\$7	400	50,000	0.80%	1,000,000	\$336,000

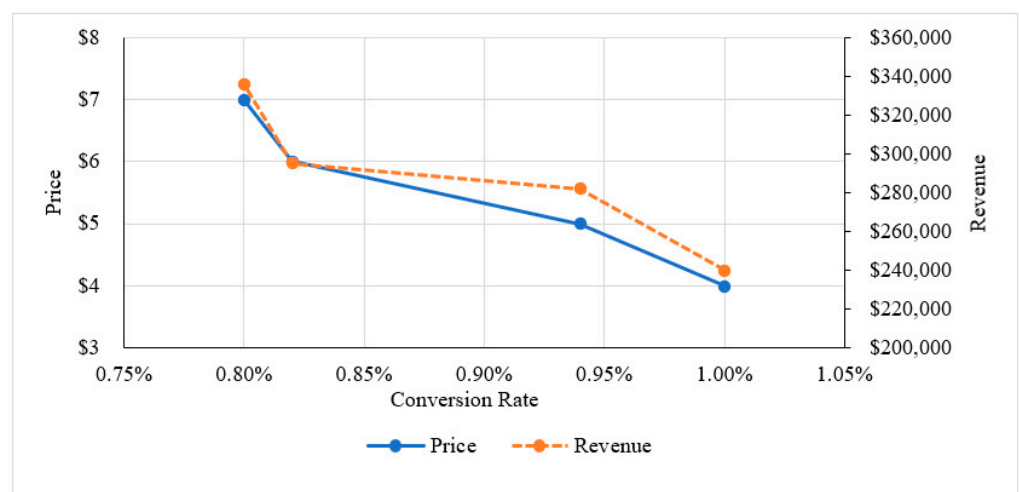


Figure 1. Empirical Demand Curve.

3. Discussions

3.1. Notable Advantages

There are notable advantages to using the proposed framework. First, the demand schedule is derived directly from the observed link between prices and the quantity demanded. Thus, there is no need to make assumptions regarding the specification of the consumers' utility functions or budget constraints. Second, customers are not asked about their willingness to subscribe to the products through surveys, focus groups, or questionnaires. Instead, their behaviours are observed in the very environment in which they make purchase decisions. Third, it is relatively quick and inexpensive to implement. Fourth, large data samples, which provide relatively precise estimates of the conversion rates at different price points and tight confidence intervals, can be gathered and analyzed. Fifth, the generalized dogma of economic theory, psychology, or marketing science is absent. This framework is at once emphatically agnostic and specifically suited to the context in which it is applied. Sixth, it circumvents the identification problem in econometric derivations of demand schedules. In fact, the framework obviates econometrics. Lastly, it allows one to focus on only the relevant portion of the demand curve.

3.2. Zooming in on Testable Price Points

Amongst the infinite possibilities, which price points should be tested? Two points bear emphasis: first, digital games are differentiated products; second, they can be regarded as substitutes, whether perfect or imperfect. While the first point may tempt the firm to test prices that are not in the close vicinity of other games, the second may serve as a reminder to keep the prices tethered to those of the alternatives available on the market.

Thus, before experimenting with different price points, it is instructive to select them systematically. At this stage, experience, information on historical prices, focus groups, and short surveys may be used to identify how much the customers are willing to pay for different products. In essence, the objective is to identify the relative marginal utility that customers derive from playing different games. This information, in turn, informs the choice regarding the price points that are tested experimentally.

To express this formally, consider a utility-maximizing customer who consumes a necessary numeraire commodity c , digital game g , and alternative games a . Further, assume that g and a are perfect substitutes; at any point in time, the customer subscribes to only one digital game and relaxing this assumption does not change the main result. Accordingly, the customer chooses c , g , and a to maximize the log-linear utility function:

$$U = \alpha \log(c) + (1 - \alpha) \log(\beta g + \delta a) \tag{2}$$

s.t.

$$m = p_c c + p_g g + p_a a \tag{3}$$

where α is a continuous variable in the interval $[0, 1]$, which determines the proportion of the consumer's income spent on the numeraire commodity and digital games; β and δ are the marginal utilities derived from consuming g and a , respectively; m is the customer's income; and p_c , p_g , and p_a are the prices of c , g , and a , respectively. The first-order conditions obtained from maximizing Equation (3), subject to Equation (4), yield:

$$\frac{\beta}{\delta} = \frac{p_g}{p_a} \tag{4}$$

Information on β and δ can be gleaned from focus groups and carefully designed surveys, whereas p_a is directly observable. Therefore, the variable of interest p_g can be derived based on the values of β , δ , and p_a . Considering that competitors may react to the firm's decision regarding p_g , various scenarios with different values of p_a may be considered. In any case, the firm should experiment with different values of p_g with due consideration to Equation (4). As such, it should seek to maximize p_g while ensuring that $\frac{\beta}{\delta} > \frac{p_g}{p_a}$. The digital games industry, which comprises a few dominant firms producing differentiated products, may be regarded as monopolistically competitive or as an oligopoly. Thus, setting prices above marginal costs is feasible. The proposed experimental framework is effective and practical for determining the optimal price amongst a set of feasible prices.

3.3. The Costs

A short discussion of the cost of production is in order. The scaling potential of digital games is high. They can be enjoyed concurrently by millions of players. However, the marginal costs remain constant over large ranges of the size of the player base; whether there are 100,000 or 105,000 players is unlikely to influence the costs incurred by the firm. Moreover, even though the marginal costs associated with one additional subscriber are minuscule [24], they do not remain constant over the entire range of the output; beyond certain thresholds of the size of the player base, the costs tend to register step increases. For example, the firm may hire more customer support representatives to address customers' questions and concerns, employ more game designers to expand the scope of the game and make it more appealing to a broader customer base, and invest in game servers to

provide a high-performance, low-latency, and stable gaming experience. A step function aptly captures the marginal costs in these cases.

Accordingly, the firms' marginal costs can be specified as follows:

$$MC_i = \frac{\sum_{k=1}^j c_i^k \Delta x_i^k}{\Delta q_i} \quad \forall i = 1, \dots, n \tag{5}$$

where MC_i is the marginal cost over the output interval i ; c_i^k is the cost of input k over the output interval i ; Δx_i^k is the change in the quantity of the input k over the output interval i ; and Δq_i is the change in the output over interval i . Since the numerator and the denominator for each of the n intervals are constants, MC_i is also constant within the intervals [25]. In Figure 2, for example, the marginal cost increases between intervals 1, 2, and 3, but remains constant within each of the three intervals.

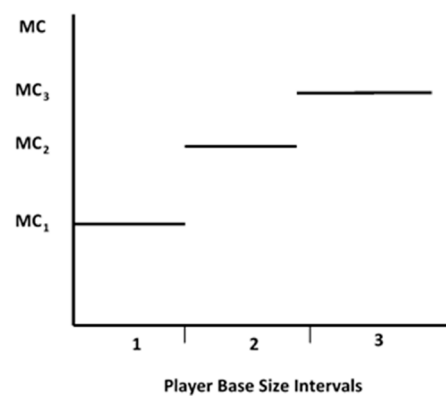


Figure 2. The Step Marginal Cost Curve.

Now that we have illustrated the empirically derived demand schedules, which may be at odds with conventional economic theory, and the marginal cost curve, which is discontinuous, it is readily observed that profit-maximizing conditions cannot be identified by employing standard optimization methods.

4. Conclusions

The characterization of a product's demand curve informs its profit-maximizing price. However, how can one derive the demand curve itself? This is the principal question addressed in this paper. Based on standard economic theory, the demand curve is derived using the customers' theoretical utility functions and budget constraints; however, these are seldom known. On the other hand, econometric approaches to estimating demand curves are fraught with identification issues. We propose an experimental framework for estimating the demand curve of digital products empirically. Focussing on digital games, we enumerate the advantages of using the said approach and illustrate why standard economic theory does not lend itself well to deriving the demand curve and the profit-maximizing price of digital products. Nevertheless, economic theory may help inform the experiments' parameters. We contend that the digital space is well-suited to determining a digital product's demand curve and, in turn, its profit-maximizing price experimentally; the experimental approach is widely applicable, yields precise estimates, and is quick and inexpensive to implement. Be that as it may, an experimental approach to iteratively optimize products, services, and processes may be challenging to entrench in an organization that resists data-driven decision-making. Gaining organization-wide support for experimentation may require analysts and data scientists to help different stakeholders understand the value of experimentation through small projects and proofs of concept. In fact, working with different stakeholders, such as marketing managers and product designers, may help calibrate experiments and align them with business objectives to glean actionable insights.

To be clear, using customer and market data in experimental frameworks may engender selection bias; it is often challenging to obtain random samples of customers and randomly assign them to the control and treatment groups. In such cases, caution is necessary when interpreting the effects of different treatments on the outcomes of interest; it is important to be heedful of these limitations. Furthermore, this paper is limited in that it uses hypothetical data for illustrative purposes; however, this points to a promising area for future research—collect real-world data and derive the empirical demand curve based on the proposed experimental approach. We hope that researchers will put this framework to the test.

Author Contributions: Conceptualization, P.V.; methodology, P.V.; writing—original draft preparation, P.V.; writing—review and editing, W.M. and X.Z. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by the National Natural Science Foundation of China, grant number 72003089.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Wu, C.-H.; Yan, Z.; Tsai, S.-B.; Wang, W.; Cao, B.; Li, X. An Empirical Study on Sales Performance Effect and Pricing Strategy for E-Commerce: From the Perspective of Mobile Information. *Mob. Inf. Syst.* **2020**, *2020*, 7561807. [[CrossRef](#)]
2. Lin, X.; Zhou, Y.-W.; Xie, W.; Zhong, Y.; Cao, B. Pricing and Product-bundling Strategies for E-commerce Platforms with Competition. *Eur. J. Oper. Res.* **2020**, *283*, 1026–1039. [[CrossRef](#)]
3. Das, D.; Jadhav, V. Non-linear Pricing in E-commerce: An Exploration. *SSRN Electron. J.* **2021**. [[CrossRef](#)]
4. Wu, J.; Zhao, C.; Yan, X.; Wang, L. An Integrated Randomized Pricing Strategy for Omni-Channel Retailing. *Int. J. Electron. Commer.* **2020**, *24*, 391–418. [[CrossRef](#)]
5. Liu, M.; Min, S.; Ma, W.; Liu, T. The adoption and impact of E-commerce in rural China: Application of an endogenous switching regression model. *J. Rural Stud.* **2021**, *83*, 106–116. [[CrossRef](#)]
6. Li, X.; Guo, H.; Jin, S.; Ma, W.; Zeng, Y. Do farmers gain internet dividends from E-commerce adoption? Evidence from China. *Food Policy* **2021**, *101*, 102024. [[CrossRef](#)]
7. Castronova, E.; Bell, M.W.; Cornell, R.; Cummings, J.J.; Emigh, W.; Falk, M.; Fatten, M.; LaFourest, P.; Mishler, N. A Test of the Law of Demand in a Virtual World. *Int. J. Gaming Comput. Simul.* **2009**, *1*, 1–16. [[CrossRef](#)]
8. Jin, D.Y.; Chee, F. Age of New Media Empires: A Critical Interpretation of the Korean Online Game Industry. *Games Cult.* **2008**, *3*, 38–58. [[CrossRef](#)]
9. Jiang, Q.; Fung, A.Y. Games with a Continuum: Globalization, Regionalization, and the Nation-State in the Development of China's Online Game Industry. *Games Cult.* **2017**, *14*, 801–824. [[CrossRef](#)]
10. Wu, L.; Liu, J. Need for control may motivate consumers to approach digital products: A social media advertising study. *Electron. Commer. Res.* **2020**. [[CrossRef](#)]
11. McCauley, B.; Nguyen, T.H.T.; McDonald, M.; Wearing, S. Digital gaming culture in Vietnam: An exploratory study. *Leis. Stud.* **2020**, *39*, 372–386. [[CrossRef](#)]
12. Kang, K.; Lu, J.; Guo, L.; Zhao, J. How to improve customer engagement: A comparison of playing games on personal computers and on mobile phones. *J. Theor. Appl. Electron. Commer. Res.* **2020**, *15*, 76–92. [[CrossRef](#)]
13. Doong, S.H.; Ho, S.-C. The impact of ICT development on the global digital divide. *Electron. Commer. Res. Appl.* **2012**, *11*, 518–533. [[CrossRef](#)]
14. Ma, W.; Grafton, R.Q.; Renwick, A. Smartphone use and income growth in rural China: Empirical results and policy implications. *Electron. Commer. Res.* **2020**, *20*, 713–736. [[CrossRef](#)]
15. Ma, W.; Zhou, X.; Liu, M. What drives farmers' willingness to adopt e-commerce in rural China? The role of Internet use. *Agribusiness* **2020**, *36*, 159–163. [[CrossRef](#)]
16. Šaković Jovanović, J.; Vujadinović, R.; Mitreva, E.; Fragassa, C.; Vujović, A. The Relationship between E-Commerce and Firm Performance: The Mediating Role of Internet Sales Channels. *Sustainability* **2020**, *12*, 6993. [[CrossRef](#)]
17. Shang, D.; Kauffman, R.J. A 2020 perspective on "Client risk informedness in brokered cloud services: An experimental pricing study". *Electron. Commer. Res. Appl.* **2020**, *41*, 100948. [[CrossRef](#)]
18. Choi, H.S.; Chen, C. The effects of discount pricing and bundling on the sales of game as a service: An empirical investigation. *J. Electron. Commer. Res.* **2019**, *20*, 21–34.

19. Gupta, V.; Gupta, L.; Dhir, S. Customer competency for improving firm decision-making performance in e-commerce. *Foresight* **2020**, *22*, 205–222. [[CrossRef](#)]
20. Hsiao, K.-L.; Chen, C.-C. What drives in-app purchase intention for mobile games? An examination of perceived values and loyalty. *Electron. Commer. Res. Appl.* **2016**, *16*, 18–29. [[CrossRef](#)]
21. Jørgensen, K. Newcomers in a Global Industry: Challenges of a Norwegian Game Company. *Games Cult.* **2019**, *14*, 660–679. [[CrossRef](#)]
22. Wang, X.; Ng, C.T. New retail versus traditional retail in e-commerce: Channel establishment, price competition, and consumer recognition. *Ann. Oper. Res.* **2020**, *291*, 921–937. [[CrossRef](#)]
23. Kumar, A. Book review: Abhijit V. Banerjee and Esther Duflo, *Good Economics for Hard Times: Better Answers to Our Biggest Problems*. *Soc. Chang.* **2020**, *50*, 327–331. [[CrossRef](#)]
24. Post, G.V. An economic model for pricing digital products. In Proceedings of the 42nd Annual Hawaii International Conference on System Sciences, HICSS, Waikoloa, HI, USA, 5–8 January 2009; pp. 1–10.
25. Kottke, M. The Anatomy of a Step Supply Function. *J. Farm Econ.* **1967**, *49*, 107–118. [[CrossRef](#)]