Proceedings of Conference on Business Venturing and Entrepreneurship, Fall 2021
Nov. 12, 2021. pp.113-117

Korean E-commerce Platform's Dashboard Style Decision Support System

염경민*
서울대학교 경영학과 박사과정
박재상**
서울대학교 경영학과 석사과정
유병준***
서울대학교 경영학과 교수

Abstract

Due to the recent COVID-19 pandemic, SMEs are forced to converge themselves into online business to cope with the rapidly changing business environment. However, due to various difficulties of becoming an online business, most SMEs choose to use services provided by the online sales platform. These platforms offer valuable support such as DSS in return for the high amount of commission fee. We analyze a novel data set from Naver Corporation's 'Smart Store' platform with the quasi-experimental method (propensity score matching technique combined with the difference in differences analysis) to analyze DSS usage and SME's performance empirically. Our results suggest that DSS usage leads to an increase in SME's sales performance in means of sales frequency and sales amount. Additionally, we have found weak support that DSS usage enables SMEs to attract customers better than those not using DSS.

Keywords: SME, DSS, quasi-experiment, propensity score matching, difference-in-differences

Ⅰ. Introduction

Since the worldwide outbreak of COVID-19, the size of the e-commerce market has grown more prominent than ever before. Consumers became afraid of offline shopping, worried about being infected with the virus, and eventually used online shopping as an alternative. In this trend of individual customers' preference for online purchasing, online sales became essential in the Business-to-Consumer(B2C) market. Naturally, Small Medium Enterprises(SMEs) started transforming their business into online-based selling(Kim, 2020). However, before converting into digital sales, there are many obstacles that SMEs must overcome before successfully transforming into an online business. One of the most significant issues SMEs face to start their business online is securing a stable online sales method. SMEs can choose to construct their independent website or utilize an online sales platform provided by major big tech firms(e.g., AliExpress, eBay, Shopify, etc.). However, due to many reasons, such as technical difficulties or the high cost of building and maintaining an independent webpage, most SMEs choose to use the convenient premade solution provided by the firms. SMEs must pay a specific commission fee ranging 5~20% to the platform company(Jia, 2016; Lucking-Reiley & Spulber, 2001).

Some may misconceive this high toll as an unfair contract to SMEs. However, e-commerce platforms provide opportunities to access a broader market share, expanding up to global markets. The platform also provides improved advertising tools and sales efforts that boost sales (Chun &

* yumok1@snu.ac.kr
** jsp0429@snu.ac.kr
*** byoo@snu.ac.kr

Kim, 2005). Some platforms extend their service efforts by providing DSS(Decision Support System) to individual sellers. For instance, Amazon provides 'FBA Business Reports' and Naver corporation's 'Biz Advisor' function in which sellers can track how their business is performing and choose the right strategy to make improvements. These dashboard-style information systems claim to assist sellers by enabling more refined merchandising activities, leading to more significant revenue. While sellers benefit from DSS and make more sales from selling their product, the platform also benefits from increased commission, forming a mutual relationship.

Nevertheless, there are still substantial questions about the effectiveness of DSS when applied to SMEs. Prior literature regarding DSS application's impact in the e-commerce field is mainly consisted of system design and integration(Berndt, 2001; Blackwell et al., 2006; Liu et al., 2009; Ulbrich, 2000) or focused upon Supply Chain Management(SCM) perspective (Leung et al., 2017; Ngai et al., 2012; Venkatadri et al., 2006). Some researchers have looked through DSS application on a large firm scale or usage in supporting customers' intention to purchase(Häubl & Trifts, 2000; Sproule & Archer, 2000). None have directly addressed the economic effect of DSS on the e-commerce platform, especially to SMEs. Regarding the unaddressed aspect of real-life effects of DSS, we raise the following research question:

Does usage of DSS in e-commerce platforms lead to a better performance of SMEs?

To address the question, we examined the relationships between the SME's DSS usage and performance from e-commerce platform transaction data provided by Naver Corporation.

Ⅱ. Data and Methodology

Our data set covers 59,840 SEMs operating on Naver Smart Store platform between September 9, 2019, and July 26, 2020(46 weeks) for empirical analysis. All stores were randomly sampled from 6 major product categories(agricultural products, household appliances, kitchen appliances, office supplies, men's apparel, and women's apparel).

To compare monthly performance differences under the usage of DSS and those who do not use DSS, e-commerce transaction records performed on the smart store platform were utilized. To conduct a quasi-experimental setting, the treatment definition was made between two groups of SMEs, namely the treatment group(i.e., SMEs with no DSS usage for three consecutive weeks and started to use DSS for three consecutive weeks) and the control group(i.e., SMEs without DSS usage for six consecutive weeks). Then, the Propensity Score Matching(PSM) and Difference in Differences(DID) combined model were then used to remove selection bias and achieve homogeneity of analysis subjects. For the PSM, we have applied a dynamic matching method in which the control group has been individually processed to match the treatment date of the experimental group.

The selection of covariates for PSM analysis of propensity scores should consider conditional independent assumptions, common support, or overlapping conditions. Selecting the right covariates is an essential step in controlling convenience and determining the quality of matching(Heckman et al., 1997; Smith & Todd, 2005). To find suitable covariates for our study, we investigated prior e-commerce related research. We utilized six following covariates based on preceding studies regarding e-commerce sales, which used variables reflecting the characteristics of SMEs. The six covariates are product category, advertisement expenditure, review number, customer rating, SME operation period, and ownership by individual or corporation.

The dependent variables for this study are four, which each respective variable represents the operation performance of SMEs and differs upon each effect measure.

Effect 1, the dependent variable, focuses upon sales frequency. This variable represents the outcome of the sales performance of each SME. We operationalize it as the number of times a customer makes a purchase action in a given period of 3weeks before intervention and three weeks after intervention(denoted by SalesNumber).

Effect 2, the dependent variable, focuses upon sales amount. This variable represents the outcome of the sales performance of each SME. We operationalize it as the total amount of product sales in a given period of 3 weeks before intervention and three weeks after intervention(denoted by SalesAmount).

Effect 3, the dependent variable, focuses upon the refund amount. This variable represents the outcome of the sales performance of each SME. When the refunded amount is smaller, SMEs will earn more revenue. We operationalize it as the total amount of refunded amount in a given period of 3weeks before intervention and three weeks after intervention(denoted by RefundAmount).

Effect 4, the dependent variable, focuses upon customer inflow rate. This variable represents how often customers visit each SME store from shopping search query results. When the product image or description successfully draws attention from customers, they will receive attention and get to be visited. We operationalize it as the average visiting rate(calculated by visitation frequency count/exposed frequency count) during a given period of three weeks before intervention and three weeks after intervention(denoted by ProductInflowRate).

Ⅲ. Data Analysis & Results

3.1. Empirical Model

PSM creates a statistical equivalence between the two groups by balancing them on observables(Brynjolfsson et al., 2010; Rosenbaum & Rubin, 1983). Logistic regression is conducted to estimate the propensity score; matching the treatment and control products is done with the Nearest Neighbor matching technique. Each SME that used DSS is matched to another product that did not use DSS by the closest distance(propensity score). As a result of the above, we have satisfactorily matched 860 SMEs in the treatment group to equivalent control group products in a 1:5 ratio, resulting in 4,300 matched SMEs in the control group. We checked the covariate balance between the treatment and control groups in the pre-and post-matching conditions. All variables used for PSM were not significantly different across the two groups of products post matching, implying statistical balance.

To analyze Effect 1, 2, 3, 4, we set up our empirical model(DID) as follows:

$$\ln(SalesNumber)_{ijt} = \beta_0 + \beta_1 Time_{ij} + \beta_2 DSSUSE_{ijt} + \beta_3 Time_{ij} * DSSUSE_{ijt} + \Theta X_{ij} + \varepsilon_{it} \quad (1)$$

$$\ln(SalesAmount)_{ijt} = \beta_0 + \beta_1 Time_{ij} + \beta_2 DSSUSE_{ijt} + \beta_3 Time_{ij} * DSSUSE_{ijt} + \Theta X_{ij} + \varepsilon_{it} \quad (2)$$

$$\ln(RefundAmount)_{ijt} = \beta_0 + \beta_1 Time_{ij} + \beta_2 DSSUSE_{ijt} + \beta_3 Time_{ij} * DSSUSE_{ijt} + \Theta X_{ij} + \varepsilon_{it} \quad (3)$$

$$\ln(ProductInflowRate)_{ijt} = \beta_0 + \beta_1 Time_{ij} + \beta_2 DSSUSE_{ijt} + \beta_3 Time_{ij} * DSSUSE_{ijt} + \Theta X_{ij} + \varepsilon_{it} \quad (4)$$

In Equation. 1, 2, 3, 4, i indicates a matched pair of SMEs, j denotes whether the SME belongs to the treatment or control group: 1 if the content is in the treatment group and 0 if the content is in the control group. t represents time(each three-week period), Timeij is the treatment dummy variable(that equals 1 if the SME is in the treatment group and 0 if the SME is in the control group). DSSUSE is a dummy variable denoting the SME's DSS usage, which takes the value 0 and 1 for periods before and post participation, respectively, for products belonging to the matched pair i. Xij represents control variables with Θ being their corresponding estimated coefficients. β0 are the differences in the baseline.

The critical parameter of interest of our study is the coefficient of the interaction term β3, which captures the change in the treatment and control group's difference which are the effect of the DSS usage.

3.2. Results

Effect 1. We find that the coefficient corresponding to the treatment effect of DSS for Effect 1 is consistently positive and significant. The result suggests that DSS positively influences SME's sales performance in sales frequency. Therefore, we find support for the effectiveness of DSS applied to SMEs. We find the effectiveness of DSS to be coefficient: 0.148(S.Err. 0.0617, *p<0.02*), which can be interpreted as when DSSUSE switches from 0 to 1, the % impact on SalesNumber is: ((exp(β3)-1)*100, thus: ((exp0.148)-1)*100=15.951 (Halvorsen & Palmquist, 1980). This implies that SMEs using DSS show a monthly sales frequency increase about 16% more than those without DSS usage.

Effect 2. We find that the coefficient corresponding to the treatment effect of DSS for Effect 2 is consistently positive and significant. The result suggests that DSS positively influences SME's sales performance in sales amount. Therefore, we find support for the effectiveness of DSS applied to SMEs. We find the effectiveness of DSS to be coefficient: 0.183(S.Err. 0.0617, $p<0.02$), which can be interpreted Same as Equation above: ((exp0.183)-1)*100= 20.081. This implies that SMEs using DSS show monthly sales increase of about 20.1% more than those without DSS usage.

Effect 3. We find that the coefficient corresponding to the treatment effect of DSS for Effect 3 is not significant ($p>0.2$). The result suggests that there is insufficient statistical evidence that DSS influences SME's sales performance in the refund amount.

Effect 4. We find that the coefficient corresponding to the treatment effect of DSS for Effect 4 is weakly supported. The result suggests that DSS may positively influence SME's sales performance in the aspect of drawing customers. We find the effectiveness of DSS to be coefficient: 0.1(S.Err. 0.051, $p<0.06$), which can be interpreted Same as Equation above: ((exp0.1)-1)*100=10.517. This implies weakly that SMEs using DSS may show an increase in monthly customer visits, about 10.5% more than those without DSS usage.

IV. Conclusion

In this study, we verified the DSS's legitimacy in a real-world e-commerce platform. By utilizing the quasi-experiment method, we confirmed that SME's DSS usage shows an increase in SME's sales performance in terms of sales frequency and sales amount. We have also found that there is not enough statistical evidence supporting that DSS usage influences customer’s refund rates. Additionally, we have discovered weak support that by utilizing DSS, SMEs can attract customers better than those not using DSS. However, a detailed analysis focusing on the phenomenon that explains how performance increased needs to be done. Because our current results are based on a pilot analysis, we will conduct further examinations on sales outcome results while increasing robustness and statistical power.

References

Berndt, D. J.(2001). Consumer decision support systems: A health care case study. *Proceedings of the Hawaii International Conference on System Sciences*, 142.

Blackwell, P., Shehab, E. M., & Kay, J. M.(2006). An effective decision-support framework for implementing enterprise information systems within SMEs. *International Journal of Production Research*, 44(17), 3533-3552.

Brynjolfsson, E., Hu, Y. J., & Smith, M. D.(2010). The longer tail: The changing shape of Amazon's sales distribution curve. *Available at SSRN 1679991.*

Chun, S. H., & Kim, J. C.(2005). Pricing strategies in B2C electronic commerce: analytical and empirical approaches. *Decision Support Systems*, 40(2), 375-388.

Halvorsen, R., & Palmquist, R.(1980). The Interpretation of Dummy Variables in Semilogarithmic Equations. *American Economic Review*, 70(3), 474-475.

Häubl, G., & Trifts, V.(2000). Consumer decision making in online shopping environments: The effects of interactive decision aids. *Marketing Science*, 19(1), 4-21.

Heckman, J. J., Ichimura, H., & Todd, P. E.(1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economic Studies*, 64(4), 605-654.

Jia, J.(2016). Managing the Revenue of Sales Platforms: Insights into Service Fees. *Production and Operations Management*, 25(6), 1026-1037.

Kim, R. Y.(2020). The Impact of COVID-19 on Consumers: Preparing for Digital Sales. *IEEE Engineering Management Review*, 48(3), 212-218.

Leung, K. H., Choy, K. L., Tarn, M. C., Cheng, S. W. Y., Lam, H. Y., Lee, J. C. H., & Pang, G. K. H.(2017). Design of a case-based multi-agent wave picking decision support system for handling e-commerce shipments. *In 2016 Portland International Conference on Management of Engineering and Technology,* 2248-2256.

Liu, S., Duffy, A. H. B., Whitfield, R. I., & Boyle, I. M.(2009). Integration of decision support systems to improve decision support performance. *Knowledge and Information Systems*, 22(3), 261-286.

Lucking-Reiley, D., & Spulber, D. F.(2001). Business-to-Business Electronic Commerce. *Journal of Economic Perspectives*, 15(1), 55-68.

Ngai, E. W. T., Leung, T. K. P., Wong, Y. H., Lee, M. C. M., Chai, P. Y. F., & Choi, Y. S.(2012). Design and development of a context-aware decision support system for real-time accident handling in logistics. *Decision Support Systems*, 52(4), 816-827.

Rosenbaum, P. R., & Rubin, D. B.(1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41-55.

Smith, J. A., & Todd, P. E.(2005). Does matching overcome LaLonde's critique of nonexperimental estimators?. *Journal of Econometrics*, 125(1–2), 305-353.

Sproule, S., & Archer, N.(2000). A buyer behaviour framework for the development and design of software agents in e-commerce. *Internet Research*, 10(5), 396-405.

Ulbrich, F.(2000). A Decision-Support Framework for Electronic Commerce in Small and Medium-sized Enterprises. *Conference Proceedings: Innovation Through Electronic Commerce IeC*, 211-221.

Venkatadri, U., Srinivasan, A., Montreuil, B., & Saraswat, A.(2006). Optimization-based decision support for order promising in supply chain networks. *International Journal of Production Economics*, 103(1), 117-130.