Unveiling the Impact of Alternative Credit Scoring Systems on Small and Medium-sized Enterprises

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ABSTRACT

This study examines the impact of Alternative Credit Scoring Systems (ACSS) on Small and Medium-sized Enterprises (SMEs) using the data from NAVER Financial. It employs mixed research methods, including switching regression analysis, treatment analysis, and interviews. The results show that utilizing ACSS and obtaining loans through the platform significantly improves SME sales. Even eligible SMEs who have yet to obtain loans would have benefited from increased sales if they received the loans. The study offers valuable insights for SMEs on how to enhance their resources and capabilities and maintain a competitive advantage in today's dynamic business landscape. It highlights the value of an integrated strategy, incorporating AI as a core competitive asset in finance and platform utilization for legitimacy and favorable entry into the financial sector by nonfinancial firms. Lastly, this research underscores how advanced financial technologies can help foster a more inclusive economy.

KEYWORDS: Alternative Credit Scoring Systems (ACSS), financial innovation, information asymmetry, small and medium-sized enterprises (SMEs)

1. Introduction

Historically, financial institutions such as banks have discriminated borrowers with biases against such characteristics as gender, race, and sexual orientation. In November 2020, Harvard Business Review reports, "financial institutions have approved fewer and smaller loans to women in decades past than to men with equivalent credit scores and income." This discrimination extends to businesses as well, with lending institutions exhibiting biases towards startups and small to medium-sized enterprises (SMEs) despite their significant contributions to job creation,

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innovation, and economic growth (Vasilescu, 2014). FICO states, "loan origination rejection rates have always been higher among micro-businesses and small and medium-sized enterprise borrowers due to the increased costs of serving customers, high-risk financial profiles, and a lack of traditional data to enable accurate loan assessment."[5] Such discriminatory practices limit the availability of resources for certain groups, leading to unequal opportunities and hindering their ability to acquire and leverage resources effectively. Overcoming these biases and ensuring fair and equitable access to financial resources becomes crucial for promoting economic growth, fostering innovation, and reducing disparities.

To facilitate efficient lending services by minimizing such biased outcomes, financial institutions are turning to artificial intelligence (AI) tools in evaluating creditworthiness of borrowers. The companies attempt to embrace innovative technologies to breakthrough the long-standing challenges in lending businesses. Back to the discrimination against female borrowers, for instance, Harvard Business Review (2020) suggests using AI as a solution because it can help shift "the proportion of loans previously made to women to be closer to the same amount as for men with an equivalent risk profile" by removing biases from data and models. As such, using AI tools in lending businesses is gaining increasing attention from lenders as well as scholars in the field due to potential benefits of increasing fairness and efficiency in lending services and fostering a more inclusive economy.

Alternative credit scoring systems (ACSS) is one of the rising tools in the financial services sector. By utilizing non-traditional data sources such as online transactions, mobile data, and social media, in addition to traditional financial data, ACSS provides a more comprehensive assessment of an individual or business's creditworthiness (Simumba et al., 2018). ACSS represents a rapidly

[5] https://www.fico.com/en/solutions/sme-lending

evolving area of innovation, and academic research attempt to identify challenges and opportunities for further innovation. For example, prior studies highlight the benefits of using alternative big data such as reducing the cost of collecting and incorporating data (Onay & Öztürk, 2018). Other studies highlight the benefits of ACSS that rely on such alternative data. For example, ACSS generates similar outcomes as traditional models (Baesens et al., 2003; Hu & Ansell, 2007), or even outperform traditional models in assessing creditworthiness (Huang et al., 2020). ACSS also helps expand the credit market and improve the well-being of the unbanked population that could not obtain loans from banks using traditional credit rating models, according to (Djeundje et al., 2021).

However, the literature seldom investigates the impact of ACSS on SMEs in particular although the benefits of using AI tools in lending services can be maximized when utilized for the SMEs (Balyuk, 2016; Bartlett et al., 2022; Helfat et al., 2023). As shown in FICO's statement, SMEs are more frequently rejected by banks mainly due to a lack of credit history. The lack of credit history leads to higher rejection or, if not, higher interest rates for the SMEs. Improved credit evaluation with more objective and representative data can lead to more loans for the SMEs, resulting in increased revenues and a more inclusive financial services provided by the banks.

To fill this gap in the literature, this study investigates the impact of ACSS on the growth of SMEs using the data provided by the NAVER Financial ("NAVER").[6] NAVER provides Smart Store Loans (SSL) to small-size sellers on the NAVER Smart Store platform. We investigate the effect of ACSS as a platform using a mixed research method combining quantitative and

[6] NAVER Financial operates as a financial platform for NAVER Corporation, which is the largest digital commerce and platform operator in Korea. It is established in 1999 as the world's first operator of the online Q&A platform. It has since expanded its business to include a search engine, shopping, news, email, and more. NAVER is one of the most visited websites in South Korea and is considered a pioneer in the country's tech industry. It is also the world's first operator of the online Q&A platform. https://www.NAVERcorp.com/.

qualitative analyses. In particular, we explore how an innovative financing tool provided by the platform business affects the sales of SMEs. We hypothesize that SMEs experience improved performance in terms of increased sales when they obtain SSL, compared to when they do not.

First, to investigate the quantitative effect of ACSS on SMEs' sales, we conduct switching regression analysis, which helps mitigate the concern of endogenous selection bias (Heckman, 1976; Lee, 1982). Switching regression analysis is a statistical technique used to examine how the relationship between variables changes based on different regimes or conditions. It is commonly employed in econometrics and other fields where there is an expectation that the relationship between variables may vary across different groups or circumstances.

In switching regression analysis, we divide the data into different subsets based on the utilization of SSL. Within each subset, a separate regression model is estimated to capture the relationship between the variables. The analysis allows for the possibility of regime switching, where the relationship between the variables differs between regimes. It provides insights into how the utilization of SSL may affect the relationship and helps identify the circumstances under which different relationships hold. Switching regression analysis also allows for more nuanced analysis by considering different regimes and accounting for potential variations in the relationship between variables across those regimes. As a result, we find that using ACSS significantly and positively impacts the sales of the SMEs on the platform. The results are consistent with prior studies that support the value of extending financial services to the underbanked (Bruhn & Love, 2014; Dupas et al., 2018).

Furthermore, by conducting treatment effect analysis, we find that the SMEs that are qualified for loans but have not obtained loans from the platform would have significantly benefited from increased sales should they have used the loans. This affirms that SMEs with the necessary resources and technical capabilities to effectively adopt and use ACSS will be better positioned to access credit and grow their businesses (Grant, 1991; Teece, 2009).

In addition, we conduct qualitative analysis using interviews, which supplement potential explanations to our findings. Our goal is to utilize the qualitative data as supplemental information and contribute to a more nuanced understanding of the impact of ACSS on the lending operations and outcomes. Enterprises operating on the NAVER SSL platform tend to lack records of revenues to prove their credit worthiness. This generally leads to high loan rejection rates from traditional loan providers. To overcome this issue and help SMEs launch their businesses with more financial resources, credit evaluators at the NAVER SSL synthesize information such as smart store sales and merchant bookings to understand the direct and indirect cash flows of the business and reflects them in the evaluation model. Consequently, despite the higher approval rate, the delinquency rate is significantly lower, proving the performance of ACSS based on non-financial data and credibility of their loan screening.

We make the following contributions to the existing literature. First, this study extends the understanding of AI's role in the financial services industry. By providing empirical evidence on the impacts of ACSS on SME performance, it provides a more nuanced understanding of the benefits and challenges associated with the implementation of ACSS.

Second, this study adds to the strategic management literature by highlighting how a platform integrates its market and nonmarket strategies using its AI capabilities and unique datasets. Specifically, we demonstrate how businesses can leverage platforms to create a conducive environment for their lawful entry into heavily regulated industries like the financial sector.[7] This paper in fact builds upon previous research in the fields of FinTech, AI, SME

[7] Although NAVER is not traditionally known as a financial company, it is venturing into the financial industry by introducing a platform that facilitates various financial services, including payment services

financing, and strategic management, thereby making a novel contribution to the literature at the intersection of these domains.

Third, our findings provide important implications for policymakers determined to promote a more inclusive financial environment and economy. It underscores the need for creating supportive regulatory frameworks that encourage such innovations while ensuring data privacy and fair lending practices.

Lastly, the study can guide practitioners such as platform managers on leveraging their AI capabilities and unique datasets in expanding their market offerings and navigating through highly regulated sectors. It provides recommendations on managing stakeholder relationships and regulatory challenges in the context of AI-based services.

In the next section, we provide a literature review. The following sections describe the model, data, and empirical results. The last section discusses the policy implications of this study in particular and concludes with guidance for future research.

2. Theoretical background

The resource-based view (RBV) posits that a firm's sustainable competitive advantage is derived from its unique resources and capabilities that are valuable, rare, inimitable, and non-substitutable (VRIN) (Barney, 1991). A recent flow of RBV studies address how AI adoption changes the sources of competitive advantage (Adner et al., 2019). This, in turn, mandates managers to develop new capabilities to stay relevant in an AI-based competitive landscape (Krakowski et al., 2022). Studies highlight how the shift to a digital era provide valuable niches

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and lending businesses.

that can be an opportunity for SMEs (Benner and Waldfogel, 2023) to overcome their disadvantages (Wormald et al., 2021).

Extending the literature, this study demonstrates how a platform can leverage its unique resources – AI capabilities and proprietary datasets – to penetrate an underserved market segment: under-banked SMEs. By showing an empirical instance of successful strategic resource deployment in a novel context (i.e., ACSS), this study extends RBV's applicability and provides fresh insights into resource valuation and usage in a digital and AI-driven landscape.

Meanwhile, recognizing the shift and embracing innovative technologies by organizations also represents "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments (i.e., dynamic capabilities) (Teece, 1997)." Organizations can leverage their internal capabilities to address and mitigate the issue of discriminatory practices. In this study, we illustrate a case in which a financial institution demonstrates its commitment to adopting innovative technologies to better serve their customers and achieve competitive advantage. This study highlights its use of AI in a lending business, which helps minimize biases in credit evaluation and thus provide more loans to SMEs that would have been ineligible for loans from traditional lending institutions such as banks. By removing biases from data and models, AI can ensure a fairer allocation of loans for borrowers regardless of the duration of their businesses (Bartlett et al., 2022).

Furthermore, this study shows that the platform not only utilizes its existing resources in a new context (i.e., market strategy) but also employs these resources to shape and influence its external regulatory environment (i.e., nonmarket strategy). Nonmarket strategies involve actions taken outside traditional market mechanisms, including regulatory and political strategies, which are particularly relevant given the regulatory challenges associated with the financial sector and

AI (Baron, 1995). Our study elucidates how a firm's resources can be mobilized not only to adapt to changing conditions but also to shape those conditions proactively. Therefore, using such a novel context, this study proposes an integrated view of market and nonmarket strategies, bridging a gap in the existing literature.

Lastly, we highlight the role of AI and big data in a lending business, illustrating an ACSS as a strategic tool to the changing landscape of the lending industry and an investment in innovative technologies to better meet customer needs and enhance organizational performance. It is in line with prior studies that support the positive impact of adopting AI in promoting competitiveness in a changing business landscape (Helfat et al., 2023). Prior studies also find that ACSSs that leverage big data and AI have already shifted the landscape of credit accessibility, particularly for underbanked or underserved segments such as SMEs (Balyuk, 2016; Bartlett et al., 2022).

In sum, by showing how a firm's adoption of an AI lending tool contributes to the firm's sustainable performance growth using an integrated view, our study contributes to the literature on strategy and innovation that are relatively sparse on the particular topic. The findings underscore the need for integrating market and nonmarket strategies and leveraging unique resources and capabilities for successful strategic maneuvering in today's rapidly evolving business environments.

3. Hypothesis development

Drawing on the theoretical foundations, this study formulates the following hypotheses to explore the impact of the AI-based ACSS on SME performance and the platform's strategy. First, the use of AI and machine learning in credit scoring aims to improve predictive accuracy and inclusivity, potentially leading to an increase in loan accessibility for SMEs. Therefore, we hypothesize:

> H1: ACSS adoption has a significant positive relationship with SMEs' sales performance.

Second, the first hypothesis implies that SMEs that have obtained loans through ACSS would experience higher sales growth compared to those who haven't. This expectation arises from the same assumption for the first hypothesis, which, in turn, can facilitate business expansion, investment, and ultimately contribute to higher sales growth. Therefore, we hypothesize,

> H2: SMEs that have obtained loans through ACSS experience significantly higher sales growth compared to those who haven't.

Lastly, in light of the platform's goal to enter the highly regulated finance sector, its nonmarket strategy is expected to play a vital role. We expect that through serving SMEs and showcasing its AI capabilities, the platform can shape its nonmarket environment, accumulate social capital, and build legitimacy. Therefore, we hypothesize:

> H3: The platform's use of nonmarket strategies, specifically through its AI-based ACSS, positively influences its capacity to reshape the regulatory environment.

Evaluating the impact of corporate strategy on regulatory changes, as proposed in H3, may be empirically challenging due to its long-term nature. Consequently, we utilize survey responses to gather qualitative data, seeking evidence that suggests guidance towards regulatory alterations.

Through testing these hypotheses, this study aims to provide empirical evidence on the impacts of ACSS on SME performance and the platform's strategic maneuvering in the highly regulated financial sector.

4. Model, data, and method

4.1. Model description

We examine the financial impact of SSLs on the performance of sellers by comparing the sales of businesses using SSLs with their counterfactual sales they would have achieved without SSLs. In order to estimate the effect of loan use on the seller's businesses, one should also consider the loan selection is determined endogenously. Heckman (1979) treats it as an omitted-variable bias and just added the user's tendency to select in the form of a control function to the model. In addition, Lee (1982) presents an endogenous switching regression model that captures discriminatory responses to two groups of users and non-users by further generalizing Heckman's model.

Following Lee's (1982) endogenous switching regression model, we divide NAVER Smart Store sellers into SSLs users and SSLs non-users and analyze their respective reactions. The endogenous switching regression model is a simultaneous equation model composed of the following three equations:

$$d = \begin{cases} 1 & e^* > \psi \\ 0 & e^* \leq \psi \end{cases} \quad (Loan\ Selection\ Model) \tag{1}$$

$$d^* = z'\gamma + e^* \tag{2}$$

$$y_1 = x_1'\beta_1 + u_1 \quad (With\ SSL\ Model\ ) \tag{3}$$

$$y_0 = x_0{}'\beta_0 + u_0 \quad (Without\ SSL\ Model\ ) \tag{4}$$

where d is a dichotomous variable to indicate the seller's selection to use SSL. This selection variable d is determined by the level of latent variable that is not observed by the outside researcher. In other words, it is determined by the unknown level ψ of the error term e in Loan Selection Model including latent variables. In Loan Selection Model, z is the explanatory variable that affects the determination of the value of d, and γ is the coefficient in Loan Selection Model. The explanatory variables z of Loan Selection Model include instrumental variables for endogenous control, and usually explanatory variables x of the equation (3) and (4).

In this model, we use *Seller Rating* assigned by NAVER.com as the instrumental variable for endogeneity control. Regardless of the overt characteristics of the sellers, NAVER.com assigns a seller rating based on the seller's business performance and activity level on the NAVER Smart Store platform. In addition, if the seller rating is high, it would be easier to use the loan since NAVER.com would pay attention to the seller. On the contrary, if the seller's rating is low, NAVER.com suspects the seller's business feasibility and it would not be easy for this seller to use the loan. Therefore, as some sellers with low ratings tend to refrain from applying for loans, others with the same low ratings still apply for loans, creating heterogeneity in loan applicants.

In the equations above, the error terms e, u_1, u_0 have zero means and the variance-covariance matrix that follow the trivariate normal distribution,

$$cov(e, u_1, u_0) = \Omega = [\sigma_1^2\ 0\ \rho_{1e}\ \sigma_1\ 0\ \sigma_0^2\ \rho_{0e}\ \sigma_0\ \rho_{1e}\ \sigma_1\ \rho_{0e}\ \sigma_0\ 1] \qquad (5)$$

where ρ_{ij} is the correlation coefficient between i^{th} and j^{th} variable and σ_i is the standard deviation of i^{th} variable. Thus, the dependence between Loan Selection Model and With SSL model (Without SSL model) is expressed as ρ_{1e} (ρ_{0e}). The two outcome models are assumed not to be interrelated. In other words, we assume that borrowers and non-borrowers belong to separate regimes, and that the sales amount between borrowers and non-borrowers is affected by the unobserved third factors such as loan selection.

Assuming no interrelations between the outcomes, the final models used for empirical tests are as follows:

$$E(d_1, x_1) = x_1{}'\beta_1 + \sigma_1\rho_1 \frac{\phi(z\prime\gamma)}{\Phi(z\prime\gamma)} \tag{6}$$

$$E(d_0, x_1) = x_1{}'\beta_1 - \sigma_1\rho_1 \frac{\phi(z\prime\gamma)}{\{1-\Phi(z\prime\gamma)\}} \tag{7}$$

$$E(d_1, x_0) = x_0{}'\beta_0 + \sigma_0\rho_0 \frac{\phi(z\prime\gamma)}{\Phi(z\prime\gamma)} \tag{8}$$

$$E(d_0, x_0) = x_0{}'\beta_0 - \sigma_0\rho_0 \frac{\phi(z\prime\gamma)}{\{1-\Phi(z\prime\gamma)\}} \tag{9}$$

As the dependent variable of both *with SSL* (equations (6) and (7)) and *without SSL* (equations (8) and (9)), y_i represents the outcome variables of the sellers using the loans and sellers who do not use the loans, respectively (i.e., *Sales Amount* in this study). The estimated coefficient of the model, β_i, refers to the impact of the sellers' characteristics on the rate of increase in *Sales Amount*. d_i is a dichotomous variable that indicates the seller's selection to use SSL. This selection variable, d_i, is determined by the level of latent variable that is not observed by the outside researcher. $\frac{\phi(z\prime\gamma)}{\Phi(z\prime\gamma)}$ is the inverse Mills ratio (IMR) to control the endogenous selection bias (Heckman, 1979). z is the explanatory variable that affects the determination of d_i, and γ is the coefficient in Loan Selection Model. Equations (6) and (9) are the results from our observation while equations (7) and (8) are the counterfactual outcomes that would have been observed if the loan-user had not utilized the loan, or conversely, the non-user had utilized the loan.

Lastly, the treatment effect of the borrowers' actual use of loans (i.e., Equation (10)), as well as non-borrowers' hypothetical use of loans (i.e., Equation (11)) are calculated as follows:

$$\hat{E}(\hat{E}(y_1|d_1, x_1)) - \hat{E}(\hat{E}(y_1|d_0, x_1)) \tag{10}$$

$$\hat{E}(\hat{E}(y_0|d_1, x_0)) - \hat{E}(\hat{E}(y_0|d_0, x_0)) \tag{11}$$

Equations (10) and (11) are used to show whether the positive impact of ACSS on SMEs' businesses. From these results, we show whether ACSS benefits all borrowers, including those who would be qualified but have not yet obtained loans.

4.2. Data

NAVER supports credit loan products for NAVER Smart Store proprietors so that online SMEs in financial blind spots can receive stable financing and focus on business growth without worrying about funding. In December 2020, NAVER partnered with Mirae Asset Capital, a specialized credit financial business in Korea, to provide the first credit loan product for online businesses using an alternative credit evaluation system. In July 2021, NAVER partnered with Woori Bank to provide a credit loan lineup that extends from the secondary financial sector to the primary financial sector.

By December 2021, the cumulative loan amount provided by NAVER exceeded KRW 120 billion (approximately 10 million USD), with an average loan amount of KRW 25.8 million (approximately 21,500 USD) and an average interest rate of 5.6% per annum. The combined loan approval rate exceeded 50%, and 24.3% of the borrowers are first-time smart store operators with less than a year of experience. Moreover, 58.5% of the borrowers received loans with more favorable terms due to their improved credit ratings through the alternative credit evaluation system, and 16.7% of the borrowers who had difficulty getting a loan were approved.

In this study, we use data on the characteristics of the NAVER Smart Store proprietors and their business activities. There are several reasons that the case of NAVER Smart Store is a suitable choice to study the impact of ACSS on SMEs. First, NAVER is a prominent online platform in South Korea and holds a significant market share. By choosing NAVER Smart Store as the platform to study, the study benefits from a large and diverse dataset of SMEs operating within a well-established and competitive e-commerce ecosystem. Second, NAVER Smart Store integrates ACSS within its lending process. This integration allows for a direct examination of how the utilization of ACSS affects SMEs' sales outcomes. By studying the specific context of NAVER Smart Store, we can gain insights into the unique dynamics and effectiveness of ACSS implementation within the platform. Third, SMEs play a vital role in the economy, and understanding the impact of ACSS on their sales performance is crucial. By focusing on NAVER Smart Store, the study can provide valuable insights and practical implications for SMEs operating in the e-commerce sector, enabling them to make informed decisions regarding their utilization of ACSS. Lastly, while the study is specific to NAVER Smart Store, the findings can potentially have broader implications for similar e-commerce platforms and SMEs operating in other contexts. Our study can contribute to the understanding of how ACSS can influence sales outcomes for SMEs in the e-commerce industry as a whole.

The sample period is from December 2020 to June 2021.[8] A total number of observations in the sample is 3,289, of which 1,923 businesses receive loans and 1,366 businesses do not. In reality, the number of businesses without loans exceeds the number of businesses with loans. To balance two groups, therefore, we sample without-loan businesses from businesses that meet the loan qualifications of NAVER Smart Store Loan even if they do not have outstanding loans.

In order to analyze the effect of loans on business activities, only the cases where loans precede business activities are considered. Accordingly, during the sample period, we separate *with loan* and *without loan* businesses to conduct switching regression analysis. Figure 1 shows

[8] We collect a random sample of 1% of the entire sellers on the platform from January 2019, but exclude observations prior to December 2020 because initially there are only few borrowers. Therefore, the final sample may be subject to a survivorship bias.

the proportion of *with loan* and *without loan* businesses.

###Insert Figure 1 about here###

As of June 2021, 2,200 businesses take out loans cumulatively, while 333 businesses take out loans in December 2020. The proportion of *with SSL* businesses in the entire sample is only 10.6% in December 2020 but reaches 63.7% in June 2021. We only analyze businesses from March 2021 onwards.

The dependent variables of both *with SSL* and *without SSL* are natural logarithms of the sales amount (*Sales Amount*). *Seller Rating* is assigned by NAVER.com, which we use as the instrumental variable for endogeneity control. Regardless of the overt characteristics of the sellers, *Seller Rating* is given based on the level of business performance and activity of the seller on the platform. The higher the seller rating, the greater the access to a loan.

The empirical tests also include other explanatory variables that may affect the sales amount; the representative category that separates the business sector of the sellers, the number of live products representing the scope of selling products, and the firm age that represents the business experience. *Firm Age* measures the duration in annual units between the registration date to NAVER Smart Store and the observation date of the data. The variable indicates the maturity of the business since registering the platform. Finally, we exclude from the sample those whose *Sales Amount, Firm Age,* and *N of Live Commerce Products*, are zero, close to zero, or missing. Table 1 reports the descriptive statistics of the sample as of June 2021.

###Insert Table 1 about here###

The number of businesses that take out loans and that do not take out loans are 1,923 and 1,366, respectively. The average sales amount of *with SSL* and *without SSL* businesses are KRW 14.07 million and KRW 14.64 million, respectively. The difference in the average sales amount between the two groups is not statistically significant, showing that the two groups are fairly homogeneous for *Sales Amount*. However, the two groups are significantly different in other categories measured by such explanatory variables as *Representative Category,*[9] *Firm Age,* and *N of Live Products*. In the case of *Seller rating,*[10] which we treat as our selection variable, the share of Grade 5 for the *without SSL* is significantly larger (77.2%) than that of Grade 1 for the *without SSL* (0.1%). This suggests a close correlation between loan use and seller rating.

4.3. Empirical methods

This study uses a mixed method combining the quantitative and qualitative approaches. Using a mixed-method approach to research helps bring depth and breadth to academic research by explaining “why” and “how” behind “what” simultaneously.

For the quantitative approach, we conduct switching regression and treatment effect analyses. Switching regressions analysis provides a convenient tool to determine the factors or conditions that drive the switching between these regimes and examine the impact of such switching on the outcomes of interest. We use switching regression analysis to take advantage of its ability to capture the heterogeneity in the data and model the distinct relationships and behaviors exhibited by different groups or segments within the sample (Lee, 1982). Using switching regression analysis is also known to alleviate endogenous issues and thus and provide more reliable empirical results (Wooldridge, 2010). Treatment effect analysis enhances our understanding of the

[9] For *Representative Category*, the top seven are selected according to the frequency, and the rest are classified as *Others*. The top seven categories are *Furniture/Interior, Digital/Home Appliances, Living/Health, Sports/Leisure, Food, Fashion Clothing, Fashion Accessories. Others* includes *Books, Relaxation/Living Conveniences, Travel/Culture, Birth/Childcare, Cosmetics/Beauty*, etc.

[10] The seller rating of NAVER Smart Store Loan has a total of six stages, and is reflected on the 2nd of every month by aggregating sales performance for the last three months. *Grade 1* is the highest rating while *Grade 5* is the lowest.

impact of ACSS by examining how eligible firms that choose not to utilize loans would hypothetically perform if they had utilized the loans.

In light of the qualitative approach, we conduct interviews with the lenders on the NAVER Smart Store platform to gather qualitative data. Conducting an interview adds depth and qualitative richness to the research findings, enhances the understanding of the empirical results, and offers valuable insights for both academic research and practitioners in the industry (Eisenhardt & Graebner, 2007). Specifically, we aim to gain a comprehensive understanding of the lenders' experiences, perceptions, and observations related to ACSS.

During the interview, a total of thirteen open-end questions are asked to the lenders, consisting of credit evaluators at the alternate credit scoring (ACS), loan providers at the Loan department, and leaders and researchers at the Policy department.[11] The responses are analyzed and discussed in **5. Findings**. The interview questions are distributed in May 2023 and the responses are collected in June 2023, providing the interviewees a month to respond. The responses provide valuable insights into the effects of ACSS on the loan approval process, its effectiveness in identifying creditworthy borrowers, the potential benefits and challenges associated with its use, and its role in creating a more inclusive lending environment via innovation.

5. Findings

5.1. The effect of ACSS on loan selection and sales

This section discusses the investigative outcomes regarding the influence of ACSS on loan selection and sales within the digital retail framework of NAVER SSL We conduct a cross-

[11] Refer to Appendix for the interview questions to the lenders.

sectional regression analysis using equations (6)-(9) and data up to June 2021, examining Loan Selection Model alongside its variants, With and Without SSL Models. In Table 2, the first column reports results for the effect of ACSS on loan selection while the second and third columns report results for the effect of ACSS on sales. Our analysis considers key determinants such as seller ratings, firm age, and product diversity to discern the nuanced effects of ACSS on sales outcomes.

###Insert Table 2 about here###

The outcomes of the Loan Selection Model (column 1) in Table 2 show that the seller ratings provided by NAVER SSL are significant factors that positively influence loan selection. More specifically, the coefficients for different seller ratings (1st/2nd, 3rd, and 4th) are positive and highly significant, indicating that higher seller ratings have a substantial positive effect on loan selection.

In addition, the coefficient for *Firm Age* is positive and significant in Loan Selection Model. It suggests that older firms are more likely to use loans. The coefficient for the number of live products is positive and highly significant in Loan Selection Model. It indicates that the more products the sellers in the sample have on sale, the more likely they decide to use the loans.

On the other hand, in With SSL Model (column 2) and Without SSL Model (column 3), the coefficients for ρ (rho) are -0.807 and -0.644, respectively, with a significance level of less than 0.1%. ρ measures the correlations between Loan Selection Model and With SSL Model and between Loan Selection Model and Without SSL Model. A significant and negative correlation between the error term of Loan Selection Model and the error term of and With SSL Model implies that the increase in sales in With SSL Model is higher when businesses are not randomly selected. While the coefficients for ρ in both the models, one with SSL and the other without SSL, are relatively close to each other, it's important to consider the potential selection bias arising from the underlying assumption. Given this, it can be inferred that borrowers who opt to utilize the loans may experience a greater increase in sales. The results support the first hypothesis that ACSS usage leads to increased sales for SMEs.

Furthermore, in With SSL Model and Without SSL Model, the coefficients for *Firm Age* are larger and statistically significant. This indicates that an age of a firm is a significant factor in influencing sales. The effect is more salient when ACSS is utilized. The coefficient for the number of live products is also positive and highly significant in With SSL Model. It indicates that having a greater number of live products positively affects sales when ACSS is utilized. However, in Without SSL Model, the coefficient becomes non-significant, suggesting that ACSS plays a role in enhancing the relationship between the number of live products and sales.

Lastly, within the representative category, the coefficients for different categories show varying effects on sales. For With SSL Model, all other things being equal, *Digital/Home Appliances, Furniture/Interior,* and *Living/Health* significantly influence *Sales Amount*. For Without SSL Model, *Digital/Home appliances, Sports/Leisure,* and *Fashion Accessories* have higher sales increase rates whereas *Food* has a lower sales increase rate. Overall, the results show that the impact of ACSS may vary depending on a specific category.

5.2. The treatment effect of ACSS with and without SSL

We compare actual outcomes derived from SSL adoption against hypothetical results that would have arisen if businesses had incorporated SSL, referencing equations (10) and (11). This process aims to gauge the treatment effect of ACSS through a two-way regression analysis, illustrating the differential in the outcome variable between the treatment group (employing ACSS) and the control group (not employing ACSS) under various assumptions. The findings are reported in Table 3.

###Insert Table 3 about here###

Assuming *with SSL*, the estimated treatment effect is 0.9789, indicating a positive impact of ACSS on the outcome variable.

Assuming *without SSL*, the estimated treatment effect is 2.3639, suggesting that it has a larger positive impact of ACSS on the outcome variable compared to the previous case. In other words, sellers who are eligible but have not taken out a loan would have benefited significantly from increased sales if they had taken out a loan from NAVER's SSL.

The overall results indicate that ACSS has a positive treatment effect on the outcome variable, with a slightly smaller effect when combined with SSL compared to when used without SSL. These findings not only support the second hypothesis but also shed more light on the effectiveness of ACSS in the context of SSL while providing insights for understanding its impact on the outcome variable.

Furthermore, Figure 2 presents further analysis on the treatment effect, providing corroborating evidence for the findings observed in Table 3. It examines the treatment effect over the sample period and compares the average treatment effects of businesses with and without SSL.

###Insert Figure 2 about here###

The results indicate that businesses utilizing SSL have an average treatment effect of 97.9%. This suggests that, on average, these businesses experience a substantial positive impact on the outcome variable as a result of utilizing ACSS in conjunction with SSL. On the other hand, businesses without SSL exhibit a higher average treatment effect of 236.4%. This implies that, on average, businesses in this group experience an even larger positive impact on the outcome variable when using ACSS without the inclusion of SSL.

Although it should be noted that some treatment effects for businesses with loans fall within the range of less than 0, it is critical to consider the overall distribution of treatment effects in both groups. In both cases, the distribution of treatment effects as a whole is clearly larger than 0, indicating that ACSS has a positive treatment effect on the outcome variable across the sample period.

Overall, these findings support the notion that utilizing ACSS, either with or without SSL, can lead to significant positive impacts on businesses. The analysis highlights the potential benefits of incorporating ACSS into the lending process, emphasizing the importance of considering the specific loan conditions, such as SSL, when examining the treatment effects.

5.3. Supplemental qualitative analysis

We conduct interviews with lenders on the platform in order to gather more insights and perspectives regarding the implementation and impact of the ACSS on the SMEs operating on the platform. The interviews are designed to explore various aspects related to ACSS, including its impact on the credit assessment process, confidence in its accuracy and reliability, factors considered in assessing creditworthiness, changes in delinquency/default rates or repayment behavior, financial performance of lenders, advantages and limitations of ACSS, inclusivity in the lending environment, potential risks or concerns, the role of policymakers, and suggestions for improvement, among others. The findings from the qualitative analysis provide explanations for our quantitative findings, and are summarized as follows.

First, it is evident that using ACSS can lead to a higher loan approval rate. This then leads to a higher sales performance and asset expansion of the SMEs compared to the traditional method of evaluating credit worthiness based on financial statements. Such an effect is enabled due to a differentiated method that ACSS uses to evaluate borrowers' creditworthiness. A loan officer at NAVER SSL describes,

> "Lenders consider revenue flow as the most important factor when evaluating the creditworthiness of SMEs. In this regard, ACSS has differentiated features for the creditworthiness of SMEs that lack financial statements. ACSS synthesizes information such as smart store sales and merchant bookings to understand the direct and indirect cash flows of the business and reflects them in the model, contributing to the sophisticated credit rating of financial companies." (Leader, ACS department at NAVER SSL)

Our earlier findings show that the borrowers, SMEs in particular who operate on the NAVER Smart Store platform and have been approved for loans and used them, see a significantly improved sales performance. It in turn supports that the method of ACSS, which is to synthesize alternative information, can be an effective tool in a lending business.

Second, using ACSS leads to a lower delinquency rate, which contributes to building a healthier financial environment for both the lenders and the borrowers. According to the researcher from the Policy department at NAVER SSL,

> "Since the launch of the Smart Store Business Loan, there have been no delinquent principal repayments for six months. According to Seo, Jung-ho, et al (2019), the delinquency rate is proportional to the credit rating. Despite the high approval rate compared to the existing loan system, the delinquency rate is significantly lower, which proves the performance of ACSS based on non-financial data, and we believe that the reliability of loan screening results is high." (Researcher, Policy department at NAVER Smart Store Loan)

The main purpose of screening borrowers is to assure that the borrowers can pay their interests and principal on time. Therefore, a low delinquency rate would represent the effectiveness of a loan approval process. Following this notion, using alternative data and AI as the ACSS at NAVER SSL can be considered highly effective and recommended for traditional lenders. In fact, the ACSS at NAVER SSL has brought some changes in the perspectives of the traditional lenders, as shown in the loan officer's remark:

> "The credit scoring model of financial companies used to be based on traditional credit information to determine whether to approve loans. However, there are areas where it is difficult to make sophisticated assessments with traditional credit scoring, which relies on past debt information, so some financial companies introduced ACSS, which reflects various non-financial information. After completing the initial loan approval process centered on credit information, the financial company that introduced ACSS changed to a process that utilizes ACSS to determine the final loan approval." (Leader, Loan department at NAVER SSL)

Third, using ACSS helps create a more inclusive financial environment. The loan market for businesses can be divided into financial loans and policy loans. In the case of financial loans provided by financial companies, lack of available information on business owners and high business closure rates causes passive lending. Moreover, second-tier financial loans are centered on high-interest loans, making it difficult for online businesses, especially SMEs, to use such loans. On the other hand, policy loans are difficult to access because the qualifications are demanding. In Korea, for example, a personal visit is mostly required to assess applicants for policy loans, but it is nearly impossible for small online businesses to satisfy such a condition. ACSS can be used to ease such a constraint and extend loans to more borrowers. A loan officer who monitors the loan process at NAVER SSL states,

> "In the case of smart store business loans using ACSS, 62% of the smart store business owners who received loans were young owners, called the MZ generation, 31% were business owners with less than one year of business experience, and 57% of the loans were upgraded or approved through ACSS as of September, 2022. As such, ACSS has eased credit constraints by improving information asymmetry, and is serving as a strong support for the growth of thin-filer businesses with a lack of financial history. It is also highly accessible, allowing users to check limits and interest rates in just one minute with their own mobile phone, and approve loans in three minutes." (Leader, Loan department at NAVER SSL)

Such an extension of loans would help provide more opportunities to SMEs in particular who would not have been able to access loans otherwise, creating a more inclusive financial atmosphere.

Fourth, a support from policy makers and regulators may bolster the use of ACSS to the benefit of SMEs and lenders. A loan officer at the Loan department says,

> "NAVER Financial is partnering with various financial companies to provide innovative financial products. We can expect active collaboration with partners only when regulatory uncertainty decreases. It would be helpful for us to promote the use of ACSS with such benefits if policymakers help create the financial environment in which lenders can freely and safely use technology and data, the basis for the realization of innovative finance." (Leader, Loan department at NAVER SSL)

Despite the absence of pertinent guidelines, the enhanced sales performance and reduced delinquency rate at NAVER SSL underscore the efficacy and value of ACSS. The results of this study could prompt policymakers to formulate appropriate guidelines, encouraging more lenders to adopt this innovation, benefiting both borrowers and lenders. Properly utilized, ACSS offers the promise of fostering a more inclusive lending landscape, particularly channeling increased financial support to SMEs. While this doesn't explicitly confirm the third hypothesis, it provides suggestive evidence and points towards a strategic direction for future efforts.

After the first interview and analyzing the outcomes, we reached out to them to ask additional questions to clarify the process of the ACSS. First, we asked about the human-machine relationship in the loan review process. The respondent said,

> "A financial company's loan underwriting process consists of many different steps, and machines contribute to just a few of them. Specifically, machines are involved in the entire process, but only in the credit scoring system (CSS). In other words, machines are used as a tool to complement credit scoring by utilizing data that is difficult for humans to understand, and then the loan underwriting process continues as before. Within the CSS category, machines are used to quantitatively assess risk to compensate for the limitations of mechanical computation, and humans operate models and strategies to improve machine performance and minimize adverse effects. Humans determine the utilization method and requirements of machine learning (ML) models in the CSS process, respond to complaints about the evaluation results generated while operating them, and continuously monitor the model/examination operation process. Based on this, the model utilization requirements will be modified and supplemented and reflected in the model improvement." (Leader, ACS department at NAVER SSL)

When asked about their internal strategy to maximize the synergy from this relationship, he said,

> "From a ML modeling perspective, it can be defined in two ways: increasing the performance of the model and minimizing the side effects of the ML model in the process. First, to improve the performance of ML models, we continuously discover features of new service information areas in the NAVER ecosystem and try new modeling techniques or technology-based development methodologies. Various measures are also taken to minimize the side effects of ML models. First, we identify business implications of ML model inputs for model operation and decide whether to utilize them. An example is the development of ML explanatory models to enhance the explanatory power of model results."" (Leader, ACS department at NAVER SSL)

These comments underscore their adept utilization of AI, machine learning, and big data to augment the shortcomings of human labor, all while recognizing the inherent limitations of such technologies. The interview results provide valuable insights into achieving a harmonious equilibrium between human labor and AI, enabling the optimization of technological benefits while fully acknowledging the distinct value of human work.

6. Discussion and conclusion

In this research, we illustrate that SMEs employing ACSS experience notable sales growth. The findings underline the significance of adopting innovative technologies for sales improvement and competitiveness in the market, particularly for SMEs that are often neglected by conventional financing systems through credit rationing (Stiglitz and Weiss, 1981).

The findings of this study have significant policy implications. For example, using ACSS can help break the vicious cycle that continues to disadvantage "thin filers", mitigate the widening financial inequality, and promote more inclusive finance. "Thin filers" lack access to credit compared to "fat filers" or "thick filers." As a result, it becomes more and more difficult for "thin filers” to accumulate sufficient credit history to provide for the lenders, further limiting the evaluation of credit scores (Smith & Henderson, 2018). In fact, where financial markets are underdeveloped, almost the entire population can be “thin filers” (Banerjee & Duflo, 2012). On the contrary, different outcomes occur for “fat filers” whose rich past transaction data helps facilitate financial services for their needs. Such informational inequality expands the financial and social gap between “fat” and “thin filers”.

From the resource-based view, the findings highlight the negative impact of historical biases and discriminatory lending practices, mainly due to information asymmetry, on access to financial resources for SMEs in particular. Therefore, the study underscores the importance of addressing these biases to promote a more inclusive and equitable environment.

Today, Fintech firms are leveraging ACSS to penetrate traditional credit markets dominated by traditional financial institutions. They can tap “thin-filer” segments because ACSS allows reasonable selection for lenders, which in turn increase their profitability (Brunnermeier et al., 2021). In addition, conventional financial institutions are also incorporating non-financial data to remain competitive. They try to avoid becoming disrupted by the untapped “long tail” segments (Anderson, 2006; Brynjolfsson et al., 2006; Christensen, 2013). FICO states, “50% of previously unscorable applicants can be accurately scored” and “Millions more consumers score high enough to qualify for credit” due to alternative data. FICO’s traditional competitors such as Experian, TransUnion, and VantageScore are also adjusting their models to use alternative data. Furthermore, other fintech firms target even narrower segments such as immigrants (e.g., Nova Credit), renters (e.g., Canopy), and non-prime borrowers (e.g., Applied Data Finance).

While the study on the impact of ACSS on SMEs' sales performance offers valuable insights, it is important to acknowledge some potential drawbacks or limitations that may exist.

For example, the study primary focuses on sales performance as the outcome variable may overlook other important dimensions of SMEs' performance, such as profitability, market share, or customer satisfaction. In addition, the study's analysis is conducted over a specific timeframe, which could limit the understanding of the long-term effects of ACSS adoption. Examining performance changes over an extended period would provide insights into the sustainability and durability of the observed effects. Last but not least, there may be other factors beyond ACSS adoption that contribute to sales growth, such as marketing strategies, competitive dynamics, or external market conditions that are not addressed in this study.

In this study, we highlight that, in the loan review process of a financial company, machines and humans have distinct roles. Machines are utilized in CSS, where they assess risk and complement human evaluation with the assessment outcomes obtained by analyzing both quantitative and qualitative data. Humans, on the other hand, are involved in determining the usage and requirements of ML models in the CSS process. They respond to complaints about evaluation results and continuously monitor the model and examination operations. Overall, the division of labor between machines and humans is designed to leverage the strengths of each and ensure an efficient and effective loan review process.

Future research may examine the long-term effects of ACSS on SMEs, considering factors such as sustainability, profitability, and overall business growth over an extended period. Future research can also compare the performance of SMEs using ACSS with those using traditional lending methods or other alternative credit scoring systems. This will help determine the relative effectiveness and benefits of ACSS in comparison to other approaches. Lastly, another area of interest can be examining the relationship between ACSS adoption and customer satisfaction and loyalty. Understanding how ACSS influences customer perceptions, trust, and loyalty towards

SMEs may provide valuable insights into the broader impact of ACSS on business performance.

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Appendix. Interview questions to the lender

1. How has the introduction of the Alternative Credit Scoring System (ACSS) impacted your loan approval process compared to traditional methods?

2. Have you noticed any differences in assessing the creditworthiness of borrowers using ACSS compared to traditional methods, and if so, how would you describe these differences?

3. How confident are you in the accuracy and reliability of ACSS in predicting borrower creditworthiness?

4. What are the main factors that lenders consider when assessing the creditworthiness of SMEs using ACSS?

5. Have you noticed any significant changes in the delinquency/default rates or repayment behavior of borrowers assessed using ACSS, and if so, what are they?

6. How has the adoption of ACSS impacted your lender's overall profitability and financial performance?

7. Please describe any specific cases or anecdotes where ACSS has identified creditworthy borrowers who may have been overlooked or underestimated by traditional credit scoring methods.

8. In your opinion, what are the main advantages or strengths of ACSS in assessing borrowers' creditworthiness at NAVER Smart Store?

9. Are there any limitations or difficulties you have encountered while using ACSS, and if so, how did you solve or mitigate them?

10. Based on your experience with ACSS, do you think it has contributed to creating a more inclusive and accessible lending environment for borrowers on NAVER Smart Store? If yes, why or why not?

11. What are some potential risks or concerns that may arise when using ACSS in lending operations?

12. What do you think about the role of policymakers in promoting and regulating the use of ACSS in the lending industry?

13. Finally, if you have any suggestions for improving NAVER's lending system, please feel free to describe them.

Figure 1. Proportion of *with loan* and *without loan* businesses

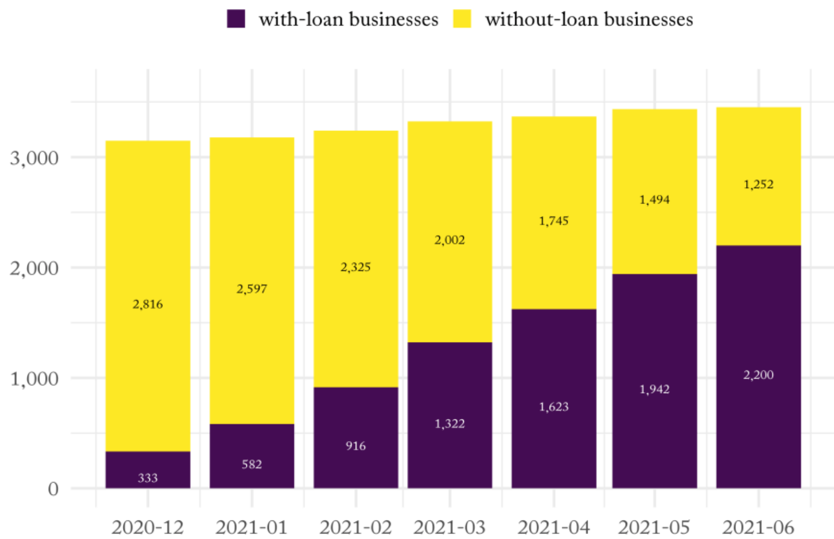

Figure 2. Distribution of treatment effects

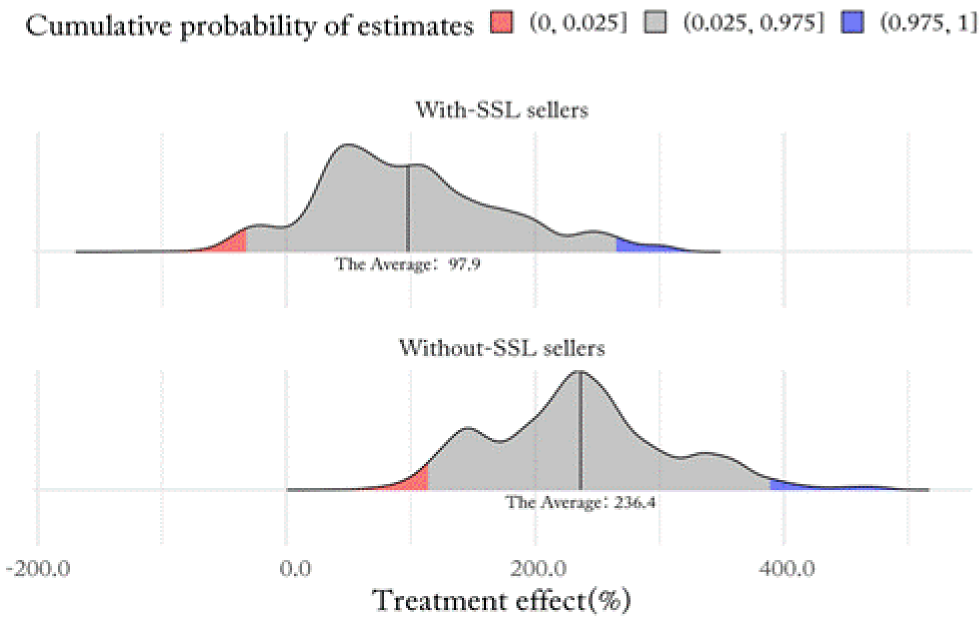

Table 1. Descriptive statistics

This table presents the descriptive statistics of the sample gathered from December 2020 to June 2021. *Sales Amount* is the natural logarithms of the sales amount in million Korean Won. *Representative Category (RC)* include subcategories such as *Furniture/Interior, Digital/Home appliance, Living/Health, Sports/Leisure, Food, Fashion Clothing, and Fashion Accessories. Firm Age* measures the duration in annual units between the registration date to NAVER Smart Store and the observation date of the data. *N of Live Commerce Products* measures the number of commerce products on sale. *Seller Rating* is given based on the level of business performance and activity of the seller on the platform. The higher the seller rating, the greater the access to a loan.

Characteristics	With SSL (N=1923)	Without SSL (N=1366)	Total (N=3289)	*p*-value
Sales Amount (KRW Mil.)				0.595[12]
N	1923	1366	3289	
Mean (SD)	14.07 (26.56)	14.64 (34.67)	14.31 (30.19)	
Min	0.01	0.01	0.01	
Median	4.72	4.50	4.59	
Max	317.29	593.53	593.53	
Representative Category (RC)				< 0.001
Furniture & Interior	198 (10.3%)	156 (11.4%)	354 (10.8%)	
Life & Health	559 (29.1%)	219 (16.0%)	778 (23.7%)	
Food	264 (13.7%)	70 (5.1%)	334 (10.2%)	
Digital & Home Appliance	148 (7.7%)	375 (27.5%)	523 (15.9%)	
Fashion Clothing	161 (8.4%)	57 (4.2%)	218 (6.6%)	
Fashion Accessories	202 (10.5%)	172 (12.6%)	374 (11.4%)	
Sports & Leisure	174 (9.0%)	160 (11.7%)	334 (10.2%)	
Others	217 (11.3%)	157 (11.5%)	374 (11.4%)	
Firm Age				< 0.001
N	1923	1366	3289	
Mean (SD)	2.64 (1.83)	2.05 (1.89)	2.40 (1.87)	
Min	0.11	0.00	0.00	
Median	2.12	1.37	1.88	
Max	9.23	9.22	9.23	
N of Live Commerce Products				< 0.001
N	1923	1366	3289	
Mean (SD)	782.99 (3781.43)	306.59 (2336.45)	585.13 (3268.03)	
Min	1.00	1.00	1.00	
Median	75.00	20.00	44.00	
Max	50000.00	49558.00	50000.00	
Seller Rating				< 0.001
Grade 1	3 (0.2%)	1 (0.1%)	4 (0.1%)	
Grade 2	500 (26.0%)	71 (5.2%)	571 (17.4%)	
Grade 3	581 (30.2%)	92 (6.7%)	673 (20.5%)	
Grade 4	511 (26.6%)	147 (10.8%)	658 (20.0%)	
Grade 5	328 (17.1%)	1055 (77.2%)	1383 (42.0%)	

[12] The p-value of the ANOVA analysis on the average in sales amount is 0.595.

Table 2. Effects of ACSS on loan selection and sales

This table presents the effects of ACSS on sales, considering Loan Selection Model and its two variations: with and without the SSL Model. Endogenous switching regression analysis is conducted for cross-sectional data at each period. The dependent variable for Loan Selection Model is the loan usage of the SMEs operating on the platform and, for With and Without SSL Models, *Sales Amount*, a natural logarithm of sales amount in million Korean Won. The table includes coefficients and standard errors (in parentheses) for the following explanatory variables: *Seller Rating* is given based on the level of business performance and activity of the seller on the platform. The higher the seller rating, the greater the access to a loan. *Firm Age* measures the duration in annual units between the registration date to NAVER Smart Store and the observation date of the data. *N of Live Commerce Products* measures the number of commerce products on sale. *RC* refers to representative categories, such as *Furniture/Interior, Digital/Home appliance, Living/Health, Sports/Leisure, Food, Fashion Clothing, and Fashion Accessories.* Significance levels are denoted as follows: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.1$.

	Loan Selection Model	With SSL Model	Without SSL Model
Seller Rating: 1st/2nd	2.2165 ***		
	(0.0657)		
Seller Rating: 3rd	1.9089 ***		
	(0.0755)		
Seller Rating: 4th	1.2236 ***		
	(0.066)		
σ		1.6293 ***	1.6921 ***
		(0.0275)	(0.0407)
ρ		-0.8067 ***	-0.6444 ***
		(0.0175)	(0.0343)
Firm age	0.0612 *	0.2384 ***	0.1279 ***
	(0.0303)	(0.0482)	(0.039)
N of live products	0.0543 ***	0.0463 *	-0.0096
	(0.014)	(0.0185)	(0.0259)
RC: Furniture/Interior	-0.0127	-0.4688 **	0.1856
	(0.1056)	(0.1475)	(0.1638)
RC: Digital/Home appliance	-0.8057 ***	0.9063 ***	0.4465 **
	(0.1068)	(0.1582)	(0.1405)
RC: Living/Health	-0.1444	-0.4701 ***	-0.1747
	(0.093)	(0.124)	(0.1477)
RC: Sports/Leisure	-0.3171 **	0.233	1.0584 ***
	(0.1074)	(0.1604)	(0.1635)
RC: Food	0.199 †	-0.335 *	-0.8346 ***
	(0.1134)	(0.1459)	(0.2029)
RC: Fashion Clothing	-0.2037	0.3071 †	-0.0867
	(0.1303)	(0.1589)	(0.2273)
RC: Fashion Accessories	-0.268 *	-0.0113	0.849 ***
	(0.1095)	(0.147)	(0.1663)
Constant	-0.9143 ***	15.6023 ***	14.2203 ***
	(0.0897)	(0.1367)	(0.1296)

Table 3. Treatment effect via a two-way regression analysis

This table presents the treatment effect as assessed through a two-way regression analysis. The dependent variable is *Sales Amount,* a natural logarithm of sales amount in million Korean Won. Results are delineated based on assumptions "with SSL" and "without SSL." The derived treatment effect is presented in coefficients while standard errors are enclosed in parentheses.[13] The values in brackets represent standard deviations.

	Assuming *with SSL*	Assuming *without SSL*	Treatment effect
With SSL	15.1564	14.1775	0.9789
	[0.9441]	[0.3998)	(0.0097)
Without SSL	17.6596	15.2957	2.3639
	[0.9214]	[0.3613]	(0.0085)

[13] In the provided data, the figures within brackets in the first two columns represent the standard deviations for the coefficients in those columns, denoted as s1 and s2, respectively. Meanwhile, the value enclosed in parentheses in the third column is derived from the formula$\left(\frac{S_1{}^2}{n^1}+\frac{S_2{}^2}{n^2}\right)^{\frac{1}{2}}$.