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The Impact of Korea Credit Guarantee Fund's Value-up Program on SME Employment and Growth: An Evaluation Using PSM-DID Methodology*

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This study addresses the research question: "What are the causal effects of proactive restructuring programs on SME employment and financial performance?" We empirically analyze the effects of Korea Credit Guarantee Fund's Value-up Program on employment and financial performance of small and medium-sized enterprises (SMEs). The Value-up Program represents a proactive approach to corporate restructuring, intervening before firms face severe financial distress, in contrast to traditional ex-post restructuring that occurs after insolvency has materialized.

This study employed PSM-DID methodology combining Propensity Score Matching (PSM) and Difference-in-Differences (DID) for 2,085 SMEs with consecutive financial statements from 2019 to 2024. Through this approach, we controlled for selection bias due to both observable characteristics and unobservable time-invariant characteristics to estimate the pure treatment effect of the Value-up Program. The analysis sample consisted of 97 companies that participated in the 2021 Value-up Program (treatment group) and 1,988 companies selected as preliminary candidates but did not participate (control group). The analysis results showed that the Value-up Program had a strong effect on SME job creation, with significant employment increases of 20.66% ($p < 0.05$) in PSM analysis and 13.4% ($p < 0.05$) in PSM-DID analysis. In terms of sales growth, PSM-DID analysis showed a significant improvement of 17.2% ($p < 0.01$). Among profitability indicators, ROA increased by 1.30%p ($p < 0.05$), showing significant improvement, while operating margin and ROE did not achieve statistical significance. Additionally, insolvency risk analysis confirmed a significant prevention effect of 4.8%p ($p < 0.01$) based on ATE. Robustness tests including parallel trend assumption tests and placebo tests yielded consistent results, ensuring the reliability of the analysis.

This study contributes to the literature by providing the first empirical evidence on the effectiveness of proactive restructuring policies in the Korean context. Our findings suggest that early intervention through

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the Value-up Program generates positive employment and growth effects, though the comparison is limited to firms within the pre-selected candidate pool. The results highlight the importance of considering employment effects in SME support policy design and evaluation. However, as the analysis was conducted during the program support period, long-term effects after program completion remain to be examined in future research.

Keyword: Korea Credit Guarantee Fund, Value-up Program, PSM-DID, SME Policy Effect, Job Creation

Ⅰ. Introduction

This study investigates the causal effects of proactive restructuring programs on SME employment and financial performance, focusing on the Korea Credit Guarantee Fund's Value-up Program. Small and medium-sized enterprises (SMEs) play a pivotal role as key economic players in Korea's national economic development. As of the end of 2023, the total number of business entities was 6,238,580 (an increase of 1.6% from the previous year), and the number of employees was 25,321,526 (an increase of 0.4%), demonstrating sustained growth. However, SMEs face structural limitations compared to large enterprises, having relatively lower capital and creditworthiness, which constrains their financial access. Particularly during management crises, they face difficulties in obtaining appropriate funding and professional restructuring support.

To address these issues, the government has established various SME support policies. Among them, the credit guarantee system has become a key policy instrument for facilitating funding for SMEs with insufficient collateral capacity. The Korea Credit Guarantee Fund was established in June 1976 as a special corporation under the Korea Credit Guarantee Fund Act, with the purpose of facilitating corporate financing by guaranteeing debts of companies with weak collateral capacity, thereby contributing to the establishment of sound credit order and balanced national economic development.

Traditional corporate restructuring has primarily focused on ex-post measures conducted after insolvency has deepened. However, ex-post restructuring conducted when corporate value has already been significantly damaged has been continuously criticized for low recovery success rates and high social costs. Academic literature has consistently documented the limitations of traditional ex-post restructuring, including low recovery rates and substantial value destruction during formal bankruptcy procedures (Hotchkiss, 1995; Altman et al., 2019). Recognizing these limitations, the importance of proactive restructuring that detects and responds to corporate financial difficulties early has recently been emphasized.

The Korea Credit Guarantee Fund has introduced the Value-up Program in response to these policy demands. The Value-up Program is defined as "a recovery support program to enhance continuing enterprise value and prevent insolvency by providing solutions necessary for corporate improvement led by the Korea Credit Guarantee Fund for SMEs with growth potential but temporarily vulnerable management conditions."

However, accurately evaluating the effects of such policy finance programs is not an easy task. Systematic differences may exist between program participants and non-participants not only in observable characteristics but also in unobservable characteristics, and such selection bias makes accurate estimation of policy effects difficult. Therefore, rigorous analytical methodologies that can appropriately control for such selection bias are necessary to identify the true effects of policies.

This study aims to empirically analyze the effects of the Korea Credit Guarantee Fund's Value-up Program on SME employment and financial performance using PSM-DID methodology. In particular, by matching non-participating companies with similar characteristics to program participants to minimize selection bias, we seek to estimate the pure treatment effect of the program and scientifically verify the effectiveness of proactive restructuring policy. The results of this study are expected to provide important policy implications for the design and operation of future SME support policies.

Ⅱ. Theoretical Background and Literature Review

2.1 Policy Finance and SME Support: Empirical Evidence

The Korea Credit Guarantee Fund (KODIT), established in 1976, serves as a key policy instrument for facilitating SME financing through credit guarantees. Extensive empirical research has examined the effectiveness of policy finance and credit guarantee programs on firm performance.

Studies on policy finance effects show mixed but generally positive results. Han and Yoon (2022) analyzed the impact of DIP (Debtor-in-Possession) financing support on SMEs under court rehabilitation using difference-in-differences methodology, finding that firms receiving DIP financial support showed approximately 25 percentage points higher sales growth compared to non-recipients. Ha et al. (2023) demonstrated that SMEs receiving indirect financial support showed better financial performance, with stronger policy effects during economic contraction periods, addressing sample selection bias through propensity score matching. Kim et al. (2023)

compared SMEs receiving government R&D support with non-recipients, demonstrating significant positive effects on both financial performance and innovation outcomes, highlighting the importance of systematic policy evaluation in understanding support program effectiveness.

Research specifically on credit guarantee systems demonstrates their role in alleviating SME financing constraints. Noh (2021) analyzed the impact of joint liability exemption on guarantee accident rates, finding that while exemption increased default probability, it did not significantly affect employment and growth outcomes between exempted and non-exempted firms.

Methodologically, recent studies have increasingly adopted rigorous causal inference approaches to address selection bias inherent in policy finance evaluation. Oh et al. (2020) evaluated online export support programs for SMEs using difference-in-differences analysis with SIMS data, finding that treated firms showed 51.8% and 85.3% higher export growth in 2018 and 2019 respectively. Kim (2016) verified the positive employment effects of job creation investment tax credits, though the impact varied by firm size and industry.

Despite this growing body of literature, most existing studies have examined traditional financing support or ex-post restructuring mechanisms, leaving a significant gap in understanding the effectiveness of proactive intervention programs like the Value-up Program that intervene before severe financial distress occurs.

2.2 Small and Medium Enterprises

Small and medium enterprises (SMEs) play an important role in the national economy and serve as the foundation of economic growth as entities for job creation and innovation activities. In Korea, SMEs account for 99% of all businesses and 89.8% of employment, playing a crucial role not only in the national economy but also in the industrial structure (KANG et al., 2020). However, their competitiveness has not improved significantly compared to large enterprises, and various efforts are needed to strengthen SME competitiveness.

SMEs tend to face relatively heavier burdens from the same regulations compared to large enterprises due to their relatively small capital scale and workforce (Shin and Lee, 2024). They also face structural difficulties in financing, human resource acquisition, and technology development, and these limitations constrain continuous growth and innovation creation. In particular, SMEs often have difficulty obtaining credit loans from financial institutions due to insufficient collateral, leading to difficulties in raising funds necessary for growth (Chai, 2012).

SMEs undergo cycles of growth and decline according to internal situations and external environmental changes after establishment. These corporate characteristics or situations can be classified into corporate growth stages, and policy support also needs to differ according to corporate growth stages (Jang, 2021). Particularly, early-stage companies have very low survival rates, and start-up companies' survival probability decreases sharply within five years, highlighting the importance of early-stage support policies (Noh, 2022).

Countries recognize the importance of SMEs and seek to promote their growth through various policy support. In particular, they are working to enhance SME competitiveness by preparing various support measures including financial support, tax benefits, technology development support, and human resource development (Son, 2008). Recently, the importance of technology-based SMEs has been further emphasized in the flow of the Fourth Industrial Revolution, and enhancing SME competitiveness through technological innovation has emerged as a key task for sustainable growth of the national economy (Kim et al., 2022). Kim and Bae (2024) demonstrated that entrepreneurship education significantly enhances enterprise performance via mechanisms such as entrepreneurial self-efficacy and satisfaction, emphasizing the importance of capability development in SME support policies. Therefore, policy efforts to effectively create jobs through technology SMEs while leading the Fourth Industrial Revolution centered on technology SMEs are becoming increasingly important.

2.3 Propensity Score Matching

The most important issue in policy effect analysis is controlling selection bias (Heckman et al., 1998). Propensity Score Matching (PSM) is a statistical methodology widely used to reduce selection bias in observational studies, enabling accurate estimation of policy effects by minimizing systematic differences between treatment and comparison groups (Imbens, 2004).

PSM was first introduced by Rosenbaum and Rubin (1983) as a method that resolves selection bias for observable characteristics by summarizing multiple characteristic variables affecting treatment status into a single propensity score and matching similar subjects. The propensity score is defined as the probability of belonging to the treatment group given observed covariates and is generally estimated through logistic regression analysis (Caliendo and Kopeinig, 2008).

The main advantages of PSM are as follows. First, it can effectively resolve selection bias between experimental and control groups (Dehejia and Wahba, 2002). Second, it can solve the curse of dimensionality problem by reducing multidimensional covariates to a single-dimensional propensity score (Stuart, 2010). Third, it enables quasi-experimental analysis in observational studies where randomized experiments are not feasible (Rubin, 2006).

The PSM process generally proceeds through the following steps (Austin, 2011). First, select observable covariates that may affect treatment group assignment. Second, estimate individual observations' propensity scores through logistic regression analysis. Third, match similar subjects based on estimated propensity scores. Fourth, estimate treatment effects for the matched sample.

Matching methods include nearest neighbor matching, radius matching, and kernel matching (Smith and Todd, 2005), and matching quality can be evaluated through covariate balance (Ho et al., 2007). PSM is based on conditional independence assumptions and common support assumptions (Rosenbaum, 2002). A major limitation of PSM is its inability to control for selection bias due to unobserved variables (Pearl, 2009). To complement this limitation, PSM is often combined with Difference-in-Differences (DID) (Blundell and Costa Dias, 2009). The PSM-DID combined model can control for selection bias due to unobservable time-invariant characteristics, enabling more robust policy effect estimation (Abadie, 2005).

PSM is now a well-established core methodology in analyzing the effects of small and medium enterprise (SME) support policies, and is widely utilized in evaluating the effectiveness of various SME support programs including credit guarantees, policy funds, and R&D support (Noh, 2021; Kim and Kim, 2024).

2.4 Difference-in-Differences

Difference-in-Differences (DID) is a quasi-experimental research design method for estimating causal effects of policies or treatments, identifying pure policy effects by comparing changes over time between treatment and control groups (Card and Krueger, 1994). This method enables more robust causal inference than cross-sectional analysis or simple before-after comparisons by controlling for unobserved time-invariant characteristics.

The basic idea of DID is to remove common shocks over time by subtracting the control group's change during the same period from the treatment group's before-after change (Angrist and Pischke, 2009). The DID equation is expressed as follows.

$$Y_{it} = \alpha + \beta \cdot Treat_i \times Post_t + \gamma \cdot Treat_i + \delta \cdot Post_t + \epsilon_{it}$$

where Y_{it} is the outcome variable for individual i at time t, $Treat_i$ indicates treatment group status, $Post_t$ indicates post-treatment period, and β is the treatment effect of interest.

The core assumption of DID is the parallel trend assumption, which assumes that treatment and control groups would have shown parallel trends over time in the absence of treatment (Bertrand et al., 2004). If this assumption is violated, estimated treatment effects may be biased, making parallel trend testing essential before analysis.

The main advantages of DID are its ability to mitigate endogeneity problems by controlling for unobserved time-invariant characteristics, control for external factors by removing common shocks over time, and analyze dynamic effects of policies (Wooldridge, 2010; Autor, 2003). However, limitations exist when the parallel trend assumption is violated or when time-varying confounding variables are present (Roth et al., 2022).

Recently, extended methodologies such as dynamic effect analysis through Event Study design and robust estimation methods for multiple-period treatment situations have been developed (Callaway and Sant'Anna, 2021). DID has become a core methodology in analyzing the effects of small and medium enterprise policies, and the PSM-DID methodology combined with propensity score matching enables more robust causal inference (Blundell and Costa Dias, 2009).

2.5 Financial Performance

Financial performance refers to measuring the results of corporate management activities through financial indicators, and is the most traditional and objective method for evaluating corporate performance. Financial performance is generally evaluated in terms of growth, profitability, stability, and activity, which are measured based on corporate financial statements (Lee, 2022).

Growth is measured by sales growth rate and total asset growth rate, while profitability is measured by operating profit margin on sales, return on assets (ROA), and return on equity (ROE). Stability is measured by debt ratio and interest coverage ratio, while activity is typically represented by total asset turnover and inventory turnover (Lee, 2024).

Studies analyzing the effects of government support programs often use methodologies combining propensity score matching (PSM) and difference-in-differences (DID) to analyze SME financial performance. This is a method to minimize selection bias in order to accurately measure the net effect of policies, selecting comparison companies with similar characteristics to supported companies and comparing performance changes before and after support (Yoon et al., 2022).

Research comparing the financial performance of innovation-certified SMEs and general SMEs selected comparison companies through propensity score matching, and found that SMEs maintaining innovation certification achieved higher growth and superior profitability compared to general SMEs (Lee, 2022).

Research analyzing the impact of government R&D support on SME financial performance confirmed positive effects on growth, profitability, and stability indicators compared to before support using PSM-DID methodology (Lee, 2024). This type of financial performance analysis is used as a key evaluation indicator for objectively assessing the current state of companies and measuring the effectiveness of government support policies.

2.6 Policy Effects

Policy effects refer to evaluating whether policies implemented by governments or public institutions have achieved their intended goals, serving as an important criterion for judging policy effectiveness and efficiency. Particularly, the effects of SME support policies are academically and policy-wise important research topics because their impact on overall national economy including economic growth, job creation, and industrial structure improvement is significant (Kim and Kim, 2013).

Among SME support policies, the credit guarantee system is a representative policy finance instrument for facilitating funding for SMEs with insufficient collateral, playing a role in supplementing market failures and easing liquidity constraints (Kim et al., 2014). Jang (2021) analyzed the effects of credit guarantee support by corporate age and derived results showing greater support effects for start-up companies.

Meanwhile, propensity score matching (PSM) is widely used as an important methodology in measuring policy effects. This is an effective method for reducing selection bias between policy beneficiary and non-beneficiary groups and identifying causal relationships, useful for understanding the pure effects of government support policies (Noh, 2021). Kim and Kim (2024) empirically demonstrated that accounts receivable insurance contributes to reducing SME default rates and increasing jobs using propensity score matching methods.

Policy effect analysis serves as important evidence for setting directions for policy improvement and development. SME support policies such as the credit guarantee system should evaluate their effects in various aspects including not only corporate performance improvement but also job creation, industrial competitiveness enhancement, and regional economic development, enabling more efficient and effective policy design (Roh and Lee, 2023).

2.7 Value-up Program: A Proactive Restructuring Approach

The Value-up Program, introduced by KODIT in 2019, represents a shift from traditional ex-post restructuring to proactive intervention. Unlike conventional workout or rehabilitation procedures that occur after insolvency, this program intervenes when firms show early warning signals but retain recovery potential. The program provides three key supports: (1) management consulting and diagnosis, (2) financial restructuring through guarantee fee reductions and new funding, and (3) business reorganization assistance. This approach aligns with recent evidence that innovation orientation and business model innovation significantly enhance SME performance, particularly when supported by appropriate environmental conditions (Lee et al., 2023), suggesting that proactive interventions facilitating organizational change can generate sustainable performance improvements.

For the 2021 cohort analyzed in this study, firms were selected based on four criteria: (1) eligible industries (manufacturing, job-creating companies, innovative SMEs), (2) total credit between 1-10 billion KRW, (3) credit rating of KR7 or below, and (4) financial vulnerability indicators including 25% or more sales decline, debt ratio over 400%, or consecutive operating losses. The program provides 3-year support including consulting, preferential guarantee terms, and financial restructuring assistance.[1)]

Ⅲ. Research Methodology

3.1 Research Hypotheses

Based on the Value-up Program's design and policy objectives, this study tests the following hypotheses linking specific program components to expected outcomes:

Hypothesis 1 (Employment Effect): The Value-up Program's financial restructuring support (guarantee fee reductions, new funding, maturity extensions) will stabilize firm operations and preserve employment, leading to positive employment effects.

Hypothesis 2 (Sales Growth): Management consulting and business reorganization assistance provided by the program will enhance operational efficiency and market competitiveness, resulting in sales growth.

Hypothesis 3 (Profitability): The combined effect of financial burden reduction and operational improvements will improve profitability indicators, though effects may manifest with time lags due to restructuring processes.

These hypotheses reflect the program's mechanism of intervening before severe distress to preserve firm value while facilitating necessary adjustments for sustainable growth.

3.2 Research Subjects and Data

This study was conducted to empirically analyze the effects of the Korea Credit Guarantee Fund's Value-up Program on SME employment and financial performance. To ensure accu-

1) Detailed program operation procedures and support structures (Value-up I vs. II) are provided in Appendix Section A.1 (see Tables A.1 and A.2 for comprehensive information on KODIT's functions and program comparison).

racy and reliability of analysis, research subjects were selected according to systematic criteria. We set the analysis period from 2019 to 2024 (6 years), and panel data analysis was conducted through between-group comparison based on participation among SMEs selected as Value-up Program candidate companies in 2021.

The sample selection process proceeded through the following systematic steps, starting from 3,504 SMEs identified as Value-up Program candidate companies in 2021:

Step 1: Initial Candidate Pool (3,504 firms) - All firms meeting the program's basic eligibility criteria[2)]

Step 2: Data Continuity Screening - Retained only firms with complete financial statements across all six years (2019-2024), as consistent panel data is essential for reliable PSM-DID analysis.

Step 3: Program Participation Classification - Excluded firms that participated in Value-up Programs in 2022 or 2023, maintaining temporal consistency for the 2021 treatment identification and ensuring a clean comparison between 2021 participants and non-participants.

Step 4: Data Quality Control - Removed firms with questionable data reliability, such as negative sales figures or zero employment despite active operations, following standard data cleaning procedures for financial statement analysis.

The final analysis sample consists of 2,085 companies, determined through systematic application of data availability and quality filters. The exact breakdown between treatment and control groups reflects the actual program participation patterns observed in the data.

Data utilized in the research was extracted from the Korea Credit Guarantee Fund's internal database and includes corporate employment and financial statement information, guarantee status, and Value-up Program participation information. All data was anonymized according to the Personal Information Protection Act and Credit Information Protection Act and utilized in accordance with research ethics regulations. The analysis period was set with 2 years before Value-up Program introduction (2019-2020) as the preperiod, 2021 as the program introduction year, and the subsequent 3 years (2022-2024) as the postperiod, totaling 6 years of observation. This temporal structure reflects practical data collection constraints: the Value-up Program's operational procedures mandate collection of

2) Selection criteria: Must meet all conditions (1)-(4): (1)Industry: Manufacturing, job-creating companies, innovative SMEs, etc. (2)Scale: Total credit between 1 billion and 10 billion KRW (3)Credit rating: KR7 grade or below (4) Financial vulnerability indicators include: Growth (current year sales decreased by 25% or more), Stability (debt ratio exceeds 400%), Profitability (recorded operating losses for 2 consecutive years), Cash flow (negative operating cash flow for 2 consecutive years or interest coverage ratio below 1), and Equity capital impairment.

financial statements for the two years immediately preceding program participation (2019-2020), making data from 2018 and earlier periods difficult to obtain systematically. The post-period extends to 2024, representing the maximum available data at the time of analysis.

3.3 Variable Definition

3.3.1 Outcome Variables

This study established multiple outcome variables regarding employment, growth, and profitability to evaluate the effects of the Value-up Program from multiple perspectives. The temporal structure for variable measurement follows a consistent framework: the pre-period consists of 2019-2020 (t-2 and t-1), the treatment year is 2021 (t=0), and the post-period spans 2022-2024 (t+1 to t+3). For outcome variables, we measure changes from t-1 (2020) to t+3 (2024) rather than using t-2 (2019) as the baseline. This methodological choice is justified by the extraordinary economic disruption caused by the COVID-19 pandemic, which created substantial volatility between 2019 and 2020 across all sectors. Using 2020 year-end as the baseline provides a more stable reference point reflecting the economic conditions immediately preceding program implementation, while the 3-year post-program observation period (2021-2024) captures the full program effects during the support phase. This approach balances the need for sufficient pre-treatment data for parallel trend testing with practical measurement of program impacts under the unique economic circumstances.

1) Employment Effects

Employment Growth Rate

$$= \frac{t+3\ year\ employees\ -\ t-1\ year\ employees}{t-1\ year\ employees} \times 100$$

where t represents the program participation year (2021). To measure long-term employment effects over 3 years, we calculated the employee change rate from the year before program participation (2020) to 3 years later (2024).

2) Growth Indicators

Sales Growth Rate

$$= \frac{t+3\ year\ sales\ -\ t-1\ year\ sales}{t-1\ year\ sales} \times 100$$

We used sales growth rate as a key indicator to measure corporate growth, with long-term effects measured over 3 years, similar to employment effects.

3) Profitability Indicators

Operating Margin Change = t+3 year

Operating Margin - t-1 year Operating Margin

ROA Change = t+3 year ROA - t-1 year ROA
ROE Change = t+3 year ROE - t-1 year ROE

To measure profitability improvement effects, changes in operating margin, ROA (Return on Assets), and ROE (Return on Equity) were analyzed. Considering the characteristics of ratio indicators, changes (differences) rather than growth rates were measured.

All outcome variables were winsorized at the 1% level (top and bottom) to minimize the impact of outliers.

3.3.2 Treatment Variable

The treatment variable was defined as participation in the 2021 Value-up Program.

$$Treat_i = \begin{cases} 1 & \text{if company } i \text{ participated in the 2021 Value-up Program} \\ 0 & \text{otherwise} \end{cases}$$

Value-up Program participation was determined based on official program approval and agreement conclusion information recorded in the Korea Credit Guarantee Fund's internal system.

3.3.3 Covariates

Covariate selection followed a three-pronged approach combining theoretical considerations, empirical evidence from prior studies, and the Value-up Program's selection criteria. All covariates were measured at t-1 (2020) to avoid reverse causality and ensure they represent pre-treatment characteristics.

1) Financial Covariates

- **Firm Size Variables**: ln(Total Assets), ln(Sales) - Included based on extensive evidence that firm size affects both program participation likelihood and outcomes (Noh, 2021; Kim and Kim, 2024)
- **Financial Structure**: ln(Borrowings) - Critical for SMEs facing financial distress, as high leverage is both a selection criterion and predictor of restructuring needs
- **Profitability Indicators**: ROA, Operating Margin - Directly related to program eligibility (consecutive losses) and baseline performance measurement

2) Corporate Characteristic Covariates

- **Industry Dummies**: Manufacturing (C), Wholesale/Retail (G), Construction (F), Other Services (S) - Controls for industry-specific vulnerability to economic shocks and differential COVID-19 impacts during 2021
- **Firm Age**: Years since establishment -

Captures lifecycle effects and survival capacity, as younger firms may have different restructuring needs (Jang, 2021)

These covariates align with the program's selection criteria while capturing key determinants of firm performance. The selection was validated through balance diagnostics and variance inflation factor (VIF) testing to ensure no multicollinearity issues.

For selected covariates, Variance Inflation Factor (VIF) testing was conducted to prevent multicollinearity issues (Table 1). For continuous variables, log transformation was applied to improve distribution normality and mitigate outlier effects.

〈Table 1〉 Variance Inflation Factor (VIF) Test Results

Variable	VIF
Total Assets (log)	3.1
Sales (log)	1.4
Borrowings (log)	2.8
ROA	1.6
Operating Margin	1.6
Manufacturing dummy	2.9
Wholesale/Retail dummy	2.6
Construction dummy	1.5
Business age	1.1

Note: VIF values below 10 indicate no multicollinearity issues

3.4 Analytical Methods and Procedures

This study employed PSM-DID methodology to estimate the causal effects of the Value-up Program. The analytical approach consists of three main components: propensity score matching to address selection bias from observable characteristics, difference-in-differences analysis to control for unobservable time-invariant factors, and robustness testing to validate the reliability of results.

3.4.1 Selection Bias and Endogeneity Issues

The primary methodological challenge in evaluating the Value-up Program is selection bias arising from both the voluntary application process and the screening procedures. Companies self-select into the program based on unobservable factors such as management quality and recovery motivation, while the screening process considers qualitative factors beyond the observable financial indicators used in this analysis. To address these concerns, we employ PSM-DID methodology that controls for both observable and time-invariant unobservable characteristics affecting program participation.

3.4.2 Data Preprocessing

1) Missing Value Treatment

Missing values in financial statement items were systematically replaced with 0 using the lapply function: ifelse(is. na(x), 0, x). This approach reflects SME financial reporting practices where missing entries typically indicate zero values. For non-financial variables, missing values were imputed with appropriate defaults to maintain data completeness.

2) Outlier Treatment

Continuous variables were winsorized at the 1% level to minimize outlier impacts. Firm size variables (total assets, sales, borrowings) were log-transformed to address distribution skewness and enhance interpretability.

3.4.3 Propensity Score Estimation and Matching

Following the theoretical framework established in Section II.3, propensity scores were estimated using logistic regression with the covariates specified in Section III.3. The matching procedure employed 1:3 nearest neighbor matching without replacement to address the bias-variance trade-off inherent in matching estimators.

The choice of a 1:3 matching ratio reflects the fundamental tension between bias and variance in matching estimators. As Caliendo and Kopeinig (2008) note, while 1:1 matching minimizes bias by selecting the closest control match for each treated unit, it often results in increased variance due to smaller sample sizes. For our study with a limited treatment group of 97 firms, this variance issue becomes particularly pronounced. Stuart (2010) emphasizes that when treatment groups are small, researchers face a critical decision between match quality (favoring 1:1) and statistical precision (favoring higher ratios).

The methodological literature provides both theoretical and empirical support for our matching ratio selection. Baek and Park (2021) recommend using 2-4 controls per treated unit when the control group is sufficiently large relative to the treatment group, as is the case in our study with 1,988 potential control firms for 97 treated firms. This guidance is based on extensive simulation studies demonstrating that moderate matching ratios effectively balance bias reduction and variance minimization in finite samples. Furthermore,

Rassen et al. (2012) successfully employed 1:3 matching in their analysis of healthcare utilization effects, demonstrating the practical effectiveness of this ratio in policy evaluation contexts similar to ours.

Our choice of 1:3 represents an empirically-grounded balance between these competing concerns. This ratio allows us to utilize 291 control observations from our matched sample, enhancing the precision of our treatment effect estimates compared to 1:1 matching, while avoiding the potential bias introduction that might occur with higher ratios such as 1:5 or 1:10. The large pool of potential controls (20:1 ratio of controls to treated) ensures that the third-best matches remain of reasonable quality, as verified by our post-matching balance diagnostics.

The matching procedure used a caliper of 0.2 standard deviations of the logit propensity score, following the widely-accepted recommendation from Austin (2011), who demonstrated through Monte Carlo simulations that this specification typically achieves good bias reduction while preserving adequate sample sizes. Post-matching diagnostics confirm successful covariate balance achievement, with standardized mean differences substantially reduced across all matching variables.

3.4.4 Combined PSM-DID Implementation

The PSM-DID analysis proceeded in three steps: (1) propensity score matching to create balanced treatment and control groups, (2) difference-in-differences estimation on the matched sample, and (3) treatment effect calculation. The model specification follows:

$$Y_{it} = \alpha + \beta \cdot Treat_i \times Post_t + \gamma \cdot Treat_i + \delta \cdot Post_t + \epsilon_{it}$$

where β represents the treatment effect of interest. We estimated ATT (Average Treatment Effect on the Treated), ATC (Average Treatment Effect on the Controls), and ATE (Average Treatment Effect) to provide comprehensive policy impact assessment.

3.4.5 Robustness Testing Methods

Robustness was assessed through placebo tests using pre-treatment periods (2019-2020) and industry-specific trend controls to account for COVID-19 differential impacts across sectors. All analyses were performed using R (Version 4.5.0) with specialized packages for matching, DID estimation, and balance testing.

Ⅳ. Analysis Results

4.1 Descriptive Statistics Analysis

The analysis sample consists of 2,085 SMEs with consecutive financial statements from 2019 to 2024. Of these, 97 companies (4.7%) participated in the 2021 Value-up Program (treatment group), while 1,988 companies (95.3%) did not participate (control group).

Examining industry distribution, manufacturing accounts for 66.0% in the treatment group, which is 14.8%p higher than the

〈Table 2〉 Research Target Company Status

Category	Total	Treatment Group	Control Group
Number of Companies	2,085	97	1,988
Percentage	100.0%	4.7%	95.3%

control group (51.2%). In contrast, wholesale/retail (20.6% vs 25.8%), construction (4.1% vs 7.6%), and other services (9.3% vs 15.4%) all showed lower proportions in the treatment group. This indicates that the Value-up Program was operated with a focus on manufacturing, or manufacturing companies had relatively greater inclination to participate in the program.

In terms of firm age distribution, the average firm age of the treatment group (13.53 years) was approximately 2 years shorter than the control group (15.48 years). Particularly, there was a significant difference in maximum values, with the treatment group at 31.98

〈Table 3〉 Industry Distribution

Industry	Treatment Group		Control Group		Total	
	Companies	Ratio(%)	Companies	Ratio(%)	Companies	Ratio(%)
Manufacturing	64	66.0	1,017	51.2	1,081	51.8
Wholesale/Retail	20	20.6	513	25.8	533	25.6
Construction	4	4.1	152	7.6	156	7.5
Other Services	9	9.3	306	15.4	315	15.1
Total	97	100.0	1,988	100.0	2,085	100.0

〈Table 4〉 Firm Age Distribution

Category	Total	Treatment Group	Control Group
Average Firm Age (years)	15.39	13.53	15.48
Standard Deviation	6.97	6.33	6.98
Median (years)	13.85	11.90	13.95
Minimum (years)	4.63	4.63	6.01
Maximum (years)	59.72	31.98	59.72

〈Table 5〉 Comparison of Key Variables Before and After Matching

Variable	Before Matching		After Matching	
	Treatment Group	Control Group	Treatment Group	Control Group
N	97	1,988	97	291
Total Assets (million KRW)	5,727	6,924	5,727	6,614
Sales (million KRW)	6,627	8,957	6,627	8,478
Borrowings (million KRW)	2,816	3,093	2,816	3,179
ROA (%)	1.67	0.24	1.67	2.27
Operating Margin (%)	2.57	-0.09	2.57	3.15
Firm Age (years)	13.53	15.48	13.53	13.19

years and the control group at 59.72 years. These findings indicate that relatively young and dynamic companies participated more actively in the Value-up Program, or younger companies with high growth potential were prioritized in the program selection process.

Before matching, substantial characteristic differences were observed between treatment and control groups. The treatment group showed relatively smaller scale in total assets (8.58 vs 8.67, log values) and sales (8.63 vs 8.70, log values) compared to the control group, but demonstrated better performance in ROA (1.67% vs 0.24%) and operating margin (2.57% vs -0.09%).

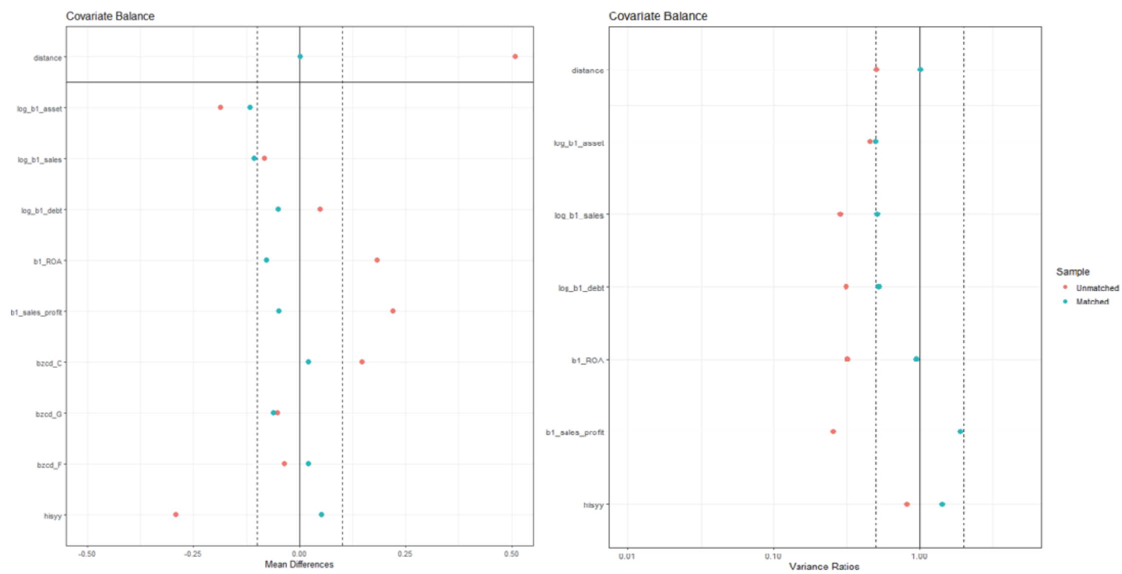
Descriptive statistics for key variables across the entire sample of 2,085 companies are shown in Table 6.

4.2 Propensity Score Matching (PSM) Results

In the PSM-selected sample of 388 companies, the proportion of the treatment group increased to 25.0% (97 companies). The distribution of key variables after matching showed similar patterns to the full sample, but with some extreme values adjusted, resulting in a more stable distribution. Figure 1 shows the

〈Table 6〉 Descriptive Statistics of Key Variables (Full Sample, N=2,085)

Variable	Mean	Std. Dev.	Median	Min	Max
Dependent Variables					
Employment Growth Rate (%)	13.67	73.50	0.00	-100.00	350.00
Sales Growth Rate (%)	36.76	91.61	17.51	-100.00	452.39
Operating Margin Change (%p)	0.44	22.45	0.81	-138.26	134.55
ROA Change (%p)	0.14	12.94	-0.12	-67.71	79.14
ROE Change (%p)	3.60	69.21	-0.73	-458.38	526.04
Covariates					
Total Assets (million KRW)	6,869	5,417	5,872	540	105,701
Sales (million KRW)	8,849	10,883	5,837	0.00	154,937
Borrowings (million KRW)	3,080	2,130	2,537	0.00	33,246
ROA (%)	0.31	9.46	1.64	-59.73	25.95
Operating Margin (%)	0.03	14.93	2.66	-114.18	23.22
Firm Age (years)	15.39	6.97	13.85	4.63	59.72
Industry Dummies					
Manufacturing Ratio	0.52	0.50	1.00	0.00	1.00
Wholesale/Retail Ratio	0.26	0.44	0.00	0.00	1.00
Construction Ratio	0.07	0.26	0.00	0.00	1.00
Other Services Ratio	0.15	0.36	0.00	0.00	1.00



〈Figure 1〉 Covariate Balance Comparison Before and After Matching (Standardized Mean Difference)

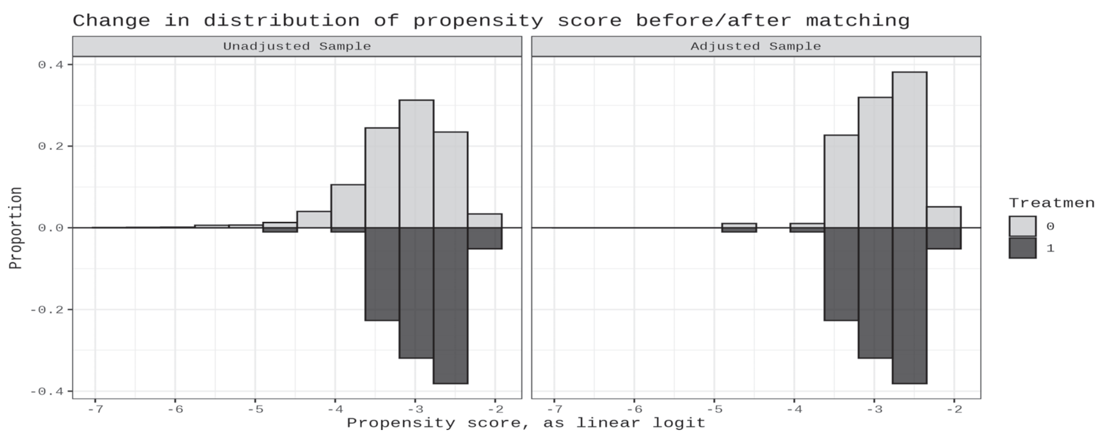
standardized mean differences of covariates before and after matching. It can be confirmed that effective matching was performed for most covariates after matching.

For firm age, the treatment group (13.5 years) and control group (13.2 years) became nearly similar, and the ROA difference also significantly decreased with the treatment group at 1.67% and control group at 2.27%. These results indicate that matching was performed effectively. Figures 2, 3, and 4 also confirm that the balance of covariates between treatment and control groups was greatly improved after matching.

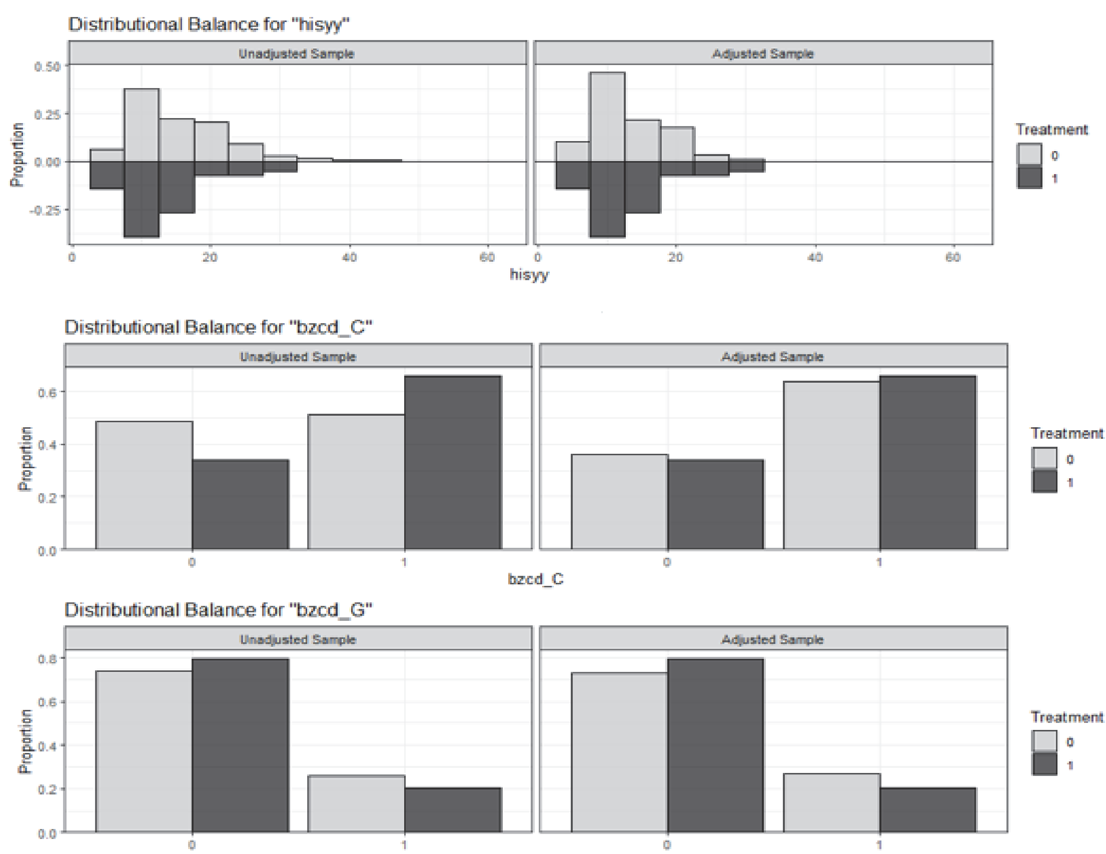
Propensity score estimation results through logistic regression analysis showed that all covariates had significant effects on Value-up Program participation. In particular, total assets, sales, borrowings scale, ROA, and operating margin were confirmed as major predictive variables. The distribution of estimated propensity scores secured sufficient common support between treatment and control groups, supporting the validity of matching.

Through nearest neighbor matching (1:3 ratio), a final 388 companies (97 treatment group, 291 control group) were selected. During the matching process, we set the caliper to 0.2 times the standard deviation of propensity scores, and companies outside the common support region were excluded from analysis.

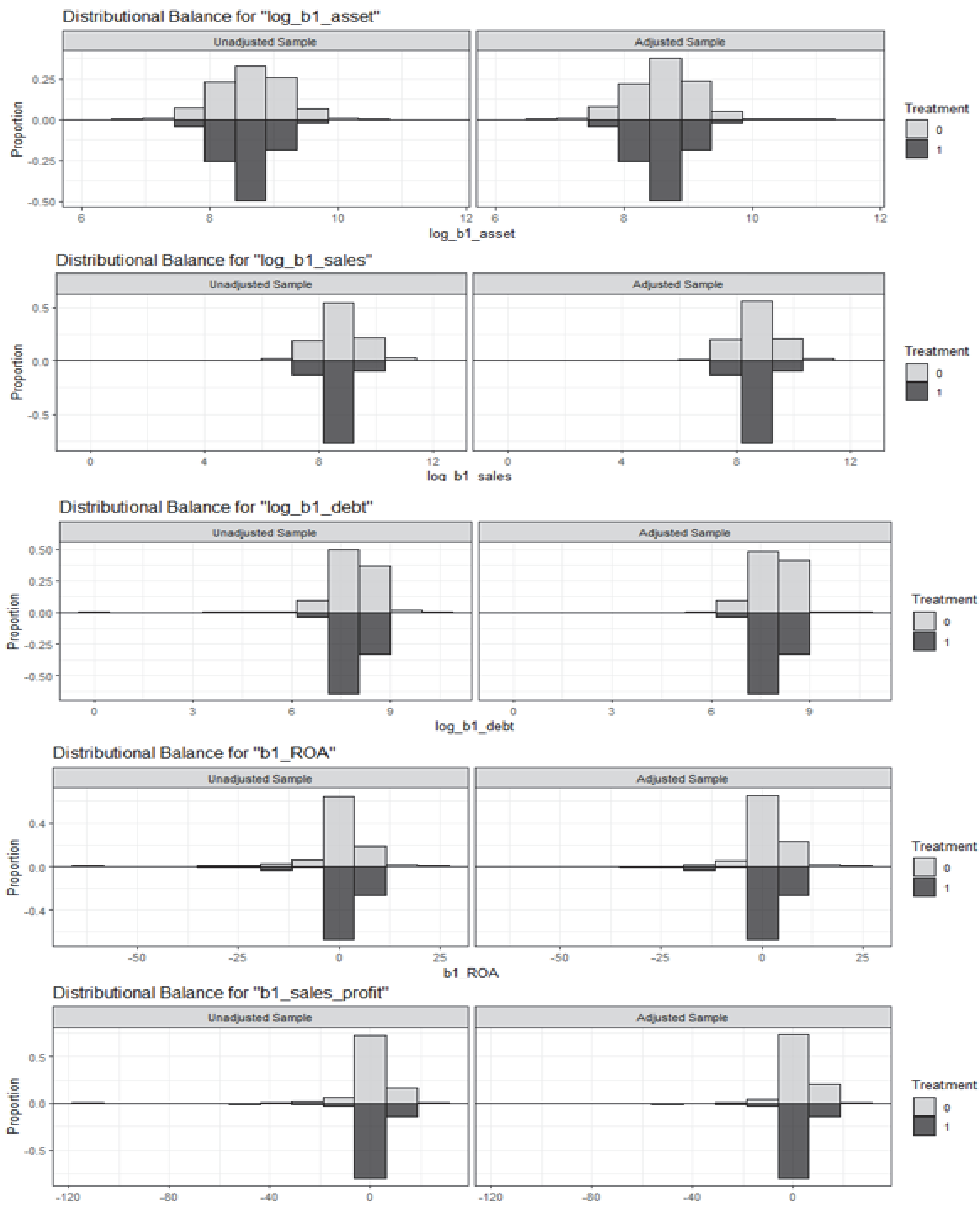
Covariate balance testing results after matching showed that balance was greatly improved for most variables. This indicates



〈Figure 2〉 Changes in Propensity Score Distribution Before and After Matching



〈Figure 3〉 Distributional Balance Test Before and After Matching (Firm Age and Industry)



〈Figure 4〉 Distributional Balance Test Before and After Matching (Financial Indicators) that propensity score matching was effective and selection bias was sufficiently controlled, making reliable treatment effect estimation possible.

4.3 Treatment Effect Analysis of Value-up Program

4.3.1 PSM-Based Treatment Effect Estimation

Treatment effect estimation results for the sample selected through propensity score matching are as follows.

Average treatment effect estimation results for the treated group showed statistically significant results only for employment effects. The employment growth rate was 20.66% (95% confidence interval: 3.30-37.96), which was statistically significant at the 1% level. In contrast, sales growth rate (14.93%), operating margin change (3.49%p), ROA change (2.05%p), and ROE change (1.90%p) were all not statistically significant.

Average treatment effect on the controls (ATC) estimation results also showed patterns consistent with ATT. For employment effects, ATC showed a significant increase of 16.73% (95% confidence interval: 1.50-32.10), confirming the positive effect of the program. In contrast, sales growth rate (16.42%) and other performance variables such as profitability indicators did not achieve statistical significance.

4.3.2 PSM-DID Combined Analysis Results

Testing the parallel trend assumption, which is a core assumption of DID analysis, showed that the assumption was satisfied for most dependent variables. Analysis of interaction terms between treatment and control groups during the pre-Value-up Program implementation period (2019-2020) showed that employment, sales, operating profit, and ROE were not statistically significant, confirming the establishment of the parallel trend assumption. However, for ROA, the p-value was 0.081, close to the general criterion ($p > 0.1$), requiring careful interpretation.

PSM-DID treatment effect estimation results

〈Table 7〉 PSM-Based Treatment Effect Estimation Results

Variable	Estimate	95% CI Lower	95% CI Upper	Significance
Employment Growth Rate (%)	20.66	3.30	37.96	*
Sales Growth Rate (%)	14.93	-4.73	34.81	
Operating Margin Change (%p)	3.49	-0.91	7.69	
ROA Change (%p)	2.05	-0.38	4.50	
ROE Change (%p)	1.90	-11.89	15.37	

Note: * $p < 0.05$. Estimate = PSM-based ATT, CI = confidence interval

〈Table 8〉 Parallel Trend Assumption Test Results

Variable	Pre-period Interaction p-value	Test Result
Employment (log)	0.642	Pass
Sales (log)	0.401	Pass
Operating Profit	0.645	Pass
ROA	0.081	Borderline*
ROE	0.524	Pass

*Larger than lenient criterion ($p > 0.05$) but smaller than general criterion ($p > 0.1$), requiring careful interpretation

〈Table 9〉 DID Estimation Results

Variable	Estimate	Std. Error	p-value	Significance
Employment (log)	0.134	0.052	0.010	*
Sales (log)	0.172	0.064	0.008	**
Operating Profit	54.321	53.013	0.306	
ROA (%p)	1.299	0.564	0.022	*
ROE (%p)	-0.632	2.634	0.810	

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

showed somewhat different patterns from PSM analysis. Employment effect was 13.4% ($p < 0.05$) and sales effect was 17.2% ($p < 0.01$), both statistically significant. Additionally, ROA increased by 1.30%p ($p < 0.05$), showing significant improvement at the 5% level. In contrast, operating profit (54.32, $p > 0.05$) and ROE (-0.63%p, $p > 0.05$) were not statistically significant.

4.4 Hypothesis Testing Results

4.4.1 Employment Effect Analysis (Hypothesis 1)

Hypothesis 1: Value-up Program participation will have a positive (+) effect on SME employment increase.

Employment effect analysis results showed consistently strong positive effects across all estimation methods. PSM analysis showed a 20.66% employment increase effect (confidence interval: 3.30 37.96%), and PSM-DID analysis showed a 13.4% ($p < 0.05$) employment increase effect. Through various robustness tests, consistent employment creation effects of approximately 13-15% were confirmed.

Therefore, **Hypothesis 1 is accepted**, and the Value-up Program has demonstrated its value as an employment-friendly growth policy.

4.4.2 Sales Growth Effect Analysis (Hypothesis 2)

Hypothesis 2: Value-up Program participation will have a positive (+) effect on SME sales growth.

Sales growth effects showed different results depending on the analysis method. PSM analysis showed a 14.93% increase but did not achieve statistical significance (confidence interval: -4.73 34.81%). In contrast, PSM-DID analysis confirmed a very significant sales growth effect of 17.2% ($p<0.01$).

Based on PSM-DID analysis results, **Hypothesis 2 is accepted**, and strong sales growth effects appeared even after controlling for time-invariant individual characteristics.

4.4.3 Profitability Improvement Effect Analysis (Hypothesis 3)

Hypothesis 3: Value-up Program participation will have a positive (+) effect on SME profitability improvement.

Profitability indicator analysis results showed inconsistent patterns. Operating margin and ROE were not statistically significant in most analyses. However, for ROA, PSM-DID analysis showed a significant improvement of 1.3%p increase ($p < 0.05$), but there are some concerns in pre-trend testing, requiring careful interpretation.

The limited profitability improvement effects reflect the characteristic that restructuring effects manifest in the long term. Therefore, **Hypothesis 3 is partially accepted**.

4.4.4 Need for Additional Analysis

To distinguish whether the employment and sales growth effects confirmed in this study represent simple scale expansion or genuine productivity improvement through qualitative growth, additional analysis is needed. It is necessary to verify whether the Value-up Program contributes to improving companies' essential competitiveness through analysis of productivity indicators such as labor productivity (sales/number of employees) or asset efficiency (sales/total assets).

Additionally, the Value-up Program is divided into Value-up (I), which is independent support from the Korea Credit Guarantee Fund, and Value-up (II), which is joint support with partner banks. Analyzing effect differences according to support methods could provide useful implications for policy design. Such segmented analysis is expected to help identify which support elements are more effective.

4.5 Robustness Testing

4.5.1 Placebo Test Results

To verify the reliability of analysis results, 〈Table 10〉 Placebo Test Results

Variable	False Treatment Effect	p-value	Test Result
Employment (log)	-0.018	0.642	Pass
Sales (log)	0.081	0.401	Pass
Operating Profit	-23.141	0.645	Pass
ROA	-1.341	0.081	Caution
ROE	-2.834	0.524	Pass

Note: Placebo test performs DID after setting treatment time to a fake year. If p-value ≥ 0.1, there are no statistically significant false effects, thus judged as "Pass"

placebo tests were conducted. Setting the period before Value-up Program implementation (2019→2020) as a virtual treatment period, analysis showed that false treatment effects did not appear in most variables.

Employment, sales, operating profit, and ROE all passed placebo tests with p〉0.1, confirming no differences in pre-trends. However, ROA showed p=0.081, close to the 10% significance level, requiring careful interpretation, which is consistent with the parallel trend assumption test results. The Value-up Program's effects on employment and sales growth can be interpreted as robust causal effects, but ROA-related results need more careful interpretation.

4.6 Additional Analysis

4.6.1 Insolvency Risk Analysis

Insolvency risk analysis using Propensity Score Weighting (PSW) methodology confirmed statistically significant insolvency prevention effects of the Value-up Program. PSW adjusts covariate imbalances between treatment and control groups through Inverse Probability of Treatment Weighting (IPTW), having the advantage of effectively controlling for unobserved selection bias.

Examining the insolvency status of analysis target companies, among 3,405 total companies, the insolvency rate of 125 treatment group companies was 16.0% (20 cases), while the insolvency rate of 3,280 control group companies was 18.1% (594 cases). After PSM matching, 375 control group companies with characteristics similar to the treatment group were selected, with their insolvency rate rising to 20.0% (75 cases).

Analyzing yearly insolvency occurrence patterns, no insolvencies occurred in the treatment group in 2021, the first year of program implementation, but small-scale insolvencies began appearing from 2022 onwards. Particularly, it peaked at 10 cases in 2023 and showed a decreasing trend to 8 cases in 2024.

Examining specific analysis results, significant insolvency reduction effects were con-

〈Table 11〉 Insolvency Status Descriptive Statistics

Category	Total Companies	Insolvent Companies	Insolvency Rate (%)	Notes
Before Matching				
Treatment Group	125	20	16.0	Value-up Participants
Control Group	3,280	594	18.1	Total Non-participants
Total	3,405	614	18.0	Total Population Basis
After Matching				
Treatment Group	125	20	16.0	Value-up Participants
Control Group	375	75	20.0	Matched Non-participants
Total	500	95	19.0	Matched Total

Note: Insolvency rate is the ratio (%) of insolvent companies to total companies in each group. Before matching is based on total population, after matching is based on 1:3 matching results.

〈Table 12〉 Insolvency Risk Analysis Results (PSM-based)

Estimation Method	Effect Estimate (%p)	95% CI Lower	95% CI Upper	Significance
ATT	-3.67	-8.53	3.06	
ATC	-5.34	-7.13	-3.57	*
ATE	-4.76	-6.54	-3.00	*

Note: * $p < 0.05$. Each figure represents the average treatment effect on insolvency risk (e.g., insolvency dummy).

firmed with ATC estimation showing -5.3%p ($p < 0.01$) and ATE estimation showing -4.8%p ($p < 0.01$). However, ATT estimation was not statistically significant. These results suggest that the Value-up Program can bring greater insolvency prevention effects to companies with relatively better financial conditions, reflecting the characteristics of proactive restructuring.

From a policy perspective, ATC estimates being larger than ATT means that among companies currently not participating in the program, there exist companies that could obtain greater insolvency prevention effects if they participated. These PSW analysis results, together with employment and sales growth effects confirmed in propensity score matching analysis, are evaluated as important evidence proving the multifaceted policy effects of the Value-up Program.

4.7 Comprehensive Analysis Results

Propensity score matching analysis confirmed strong significance (20.66%p, $p < 0.05$) only for employment effects. Other performance indicators showed positive directions but failed to achieve statistical significance. This is interpreted as showing the limitations of cross-sectional analysis.

PSM-DID analysis confirmed significant effects in more diverse indicators than PSM-only analysis. Statistically significant improvements appeared in employment (13.4%, $p < 0.05$), sales (17.2%, $p < 0.01$), and ROA (1.30%p, $p < 0.05$). This demonstrates the advantages of combining DID methodology, which can capture dynamic effects over time, with PSM methodology, which controls for selection bias.

Consistent results were derived from all robustness tests including parallel trend assumption testing and placebo testing, securing analysis reliability. Particularly, the insolvency risk reduction effect is an important finding showing the Value-up Program's additional policy value.

Ⅴ. Conclusions and Implications

5.1 Research Results Summary

This study empirically analyzed the effects of the Korea Credit Guarantee Fund's Value-up Program on SME employment and financial performance using PSM-DID methodology. Analyzing 2,085 SMEs using 6-year data from 2019-2024, the following findings were discovered.

Strong effects were confirmed in job creation with PSM analysis showing 20.66% ($p < 0.05$) and PSM-DID analysis showing 13.4% ($p < 0.05$). Sales growth showed significant improvement of 17.2% ($p < 0.01$) in PSM-DID analysis. In PSM-DID analysis, ROA improved by 1.30%p ($p < 0.05$), but operating margin and ROE were not significant. Insolvency risk analysis confirmed significant prevention effects of -4.8%p ($p < 0.01$) based on ATE. Robustness testing also derived consistent results, proving the causal effects of the Value-up Program.

5.2 Theoretical Implications

This study made academic contributions in three aspects. First, this study strengthens the empirical foundation of proactive policy intervention by conducting the first empirical analysis of proactive restructuring policy effectiveness in the Korean context. The findings demonstrate that early intervention programs can generate positive employment and growth effects, providing evidence for the effectiveness of preventive approaches over traditional ex-post restructuring.

Second, it enhanced methodological rigor in policy effect estimation by simultaneously controlling for selection bias due to observable characteristics and time-invariant characteristics through combined PSM-DID methodology. This methodological contribution addresses the limitations of previous descriptive and cross-sectional guarantee system studies by strengthening causal inference through rigorous quasiexperimental design, providing a more robust framework for policy evaluation. Third, it systematically identified the lag structure of policy effects, proving the importance of long-term perspective policy evaluation.

5.3 Policy Implications

The empirical analysis results of this study provide the following implications for SME support policy design and operation.

First, the significant job creation and insolvency prevention effects of the Value-up Program prove that proactive restructuring is more efficient than post-crisis restructuring. Since proactive intervention before companies fall into serious management crises is effective in preventing corporate bankruptcy and social costs, the government should expand proactive restructuring programs and strengthen early warning systems.

Second, the strong job creation effect (13.4-20.66%) of the Value-up Program shows that it has meaning as an employment-friendly growth policy beyond simple corporate support. Future SME support policy design should include job creation effects as key evaluation indicators and strengthen employment-friendly policy elements.

Third, the importance of long-term perspectives in SME support policy evaluation is emphasized. Policy evaluation systems should move away from short-term performance indicator focus and establish 3-5 year long-term tracking systems.

Fourth, the limited effectiveness of profitability indicators requires careful interpretation regarding the Value-up Program's characteristics and policy objectives. While employment and sales showed significant increases in this study, profitability indicators showed limited improvement, which can be interpreted not as policy failure but due to the following factors.

First, the Value-up Program's essential purpose lies in enhancing continuing enterprise value for "companies with growth potential but temporarily vulnerable management conditions." This means it is a policy supporting companies facing short-term difficulties but with long-term potential, rather than selecting and supporting companies with already excellent profitability.

Second, the time lag problem in restructuring program effect realization. Employment expansion and sales growth are relatively observable in the short term, but productivity and profitability improvements have characteristics of appearing long-term after completion of management system reorganization, workforce reallocation, and business structure reform.

Third, the need for phased approaches to quantitative and qualitative growth. For companies in crisis situations, securing corporate survival through employment stability and sales recovery first, then gradually improving efficiency and profitability, may be a rational recovery path.

From this perspective, future policy improvement directions should develop comprehensive corporate value enhancement programs beyond simple financial support, including management strategy consulting and technology innovation support, while requiring phased goal setting and long-term performance measurement in policy evaluation. Additionally, establishing customized support systems considering industryspecific and scale-specific characteristics is required.

5.4 Research Limitations and Future Research Directions

This study has the following limitations.

First, unobservable selection bias problems. Value-up Program participation is determined through companies' voluntary applications and Korea Credit Guarantee Fund screening, where unobserved factors such as CEO's management improvement will, organizational change acceptance, and companies' potential recovery capability may influence the process. While substantial selection bias was controlled through PSM-DID methodology, potential bias from these unobservable characteristics cannot be completely eliminated. Second, survivor bias problems. This study constructed a balanced panel targeting only companies with consecutive financial statements from 2019-2024. Companies that exited during this period were excluded from analysis, and if systematic differences exist in corporate survival rates by program participation, bias may occur in estimation results. Particularly considering the Value-up Program's insolvency prevention effects, such survivor bias may lead to underestimating program effects.

Third, analysis during the program support period. The Value-up Program provides 3-year support (2021-2024), and our analysis period (through 2024) captures effects while firms are still receiving program support. This means observed effects may partly reflect ongoing program assistance rather than sustainable post-program improvements. The distinction between temporary support effects and permanent structural improvements cannot be fully disentangled until firms complete the program and operate independently.

Fourth, overlap with pandemic period problems. The Value-up Program implementation period (2021) coinciding with COVID-19 pandemic presents structural limitations in completely separating external shock impacts. While partially controlled through industry-specific fixed effects, complete removal of pandemic's heterogeneous impacts on companies has limitations.

Fifth, limited generalizability due to sample restrictions. This study's findings apply specifically to firms within the pre-selected candidate pool that met the program's eligibility criteria. These firms represent a particular subset of financially vulnerable but potentially viable SMEs, and results cannot be extrapolated to: (1) the broader SME population, (2) firms in severe financial distress beyond program criteria, or (3) healthy firms not facing financial difficulties. The analysis provides valid causal estimates for the effect of the program on eligible firms, but external validity to other firm populations remains constrained.

Future research should address endogeneity resolution using instrumental variables, securing longer analysis periods, decomposing effects by program components, analyzing heterogeneous effects by industry and region, and evaluating policy efficiency through cost-benefit analysis.

This study has academic significance as the first empirical analysis of proactive restructuring policy effectiveness and policy significance in presenting effective operational measures for SME support policies. Future follow-up research is expected to derive deeper understanding of proactive restructuring policies and policy improvement measures.

References

Abadie, A. (2005). "Semiparametric Difference-in-Differences Estimators," *Review of Economic Studies,* 72(1), pp.1-19.

Altman, E. I., Hotchkiss, E., and Wang, W. (2019), *Corporate Financial Distress, Restructuring, and Bankruptcy: Analyze Leveraged Finance, Distressed Debt, and Bankruptcy,* John Wiley & Sons.

Angrist, J. D. and Pischke, J.-S. (2009), *Mostly Harmless Econometrics: An Empiricist's Companion,* Princeton University Press.

Austin, P. C. (2011). "An Introduction to Propensity Score Methods for Reducing the Effects of Confounding in Observational Studies," *Multivariate Behavioral Research,* 46(3), pp.399-424.

Autor, D. H. (2003). "Outsourcing at Will: The Contribution of Unjust Dismissal Doctrine to the Growth of Employment Outsourcing," *Journal of Labor Economics,* 21(1), pp.1-42.

Baek, Y. and Park, I. (2021), *Propensity Score Analysis Using R: Causal Inference Based on Rubin Causal Model,* Hannarae Academy, Seoul.

Bertrand, M., Duflo, E., and Mullainathan, S. (2004). "How Much Should We Trust Differences-in-Differences Estimates?," *The Quarterly Journal of Economics,* 119(1), pp.249-275.

Blundell, R. and Costa Dias, M. (2009). "Alternative Approaches to Evaluation in Empirical Microeconomics," *Journal of Human Resources,* 44(3), pp.565-640.

Caliendo, M. and Kopeinig, S. (2008). "Some Practical Guidance for the Implementation of Propensity Score Matching," *Journal of Economic Surveys,* 22(1), pp.31-72.

Callaway, B. and Sant'Anna, P. H. C. (2021). "Difference-in-Differences with Multiple Time Periods," *Journal of Econometrics,* 225(2), pp.200-230.

Card, D. and Krueger, A. B. (1994). "Minimum Wages and Employment: A Case Study of the Fast-Food Industry in New Jersey and Pennsylvania," *American Economic Review,* 84(4), pp.772-793.

Chai, H. Y. (2012). "Effect of Credit Guarantee on Performance of SMEs and Implications for Reform of Credit Guarantee Scheme in Korea," *Journal of Korean Economy Studies,* 30(2), pp.41-65.

Dehejia, R. H. and Wahba, S.(2002). "Propensity Score-Matching Methods for Nonexperimental Causal Studies," *Review of Economics and Statistics,* 84(1), pp.151-161.

Ha, S. Y., Kim, H. O., and Lee, M. J.(2023). "Effects of Indirect Financial Policy for Sustainability of Small and Medium-Sized Enterprises in Korea in Business Fluctuation Cycle," *Korean Management Consulting Review,* 23(6), pp. 223-233.

Han, D. G. and Yoon, S. M.(2022). "Effects of DIP Financing Support for SMEs on Their Performances: Using Difference in Difference Estimation," *Industrial Economics Research,* 35(2), pp.373-398.

Heckman, J. J., Ichimura, H., and Todd, P.(1998). "Matching as an Econometric Evaluation Estimator," *Review of Economic Studies,* 65 (2), pp.261-294.

Ho, D. E., Imai, K., King, G., and Stuart, E. A. (2007). "Matching as Nonparametric Preprocessing for Reducing Model Dependence in Parametric Causal Inference," *Political Analysis,* 15(3), pp.199-236.

Hotchkiss, E. S.(1995). "Postbankruptcy Performance and Management Turnover," *The Journal of Finance,* 50(1), pp.3-21.

Imbens, G. W.(2004). "Nonparametric Estimation of Average Treatment Effects Under Exogeneity: A Review," *Review of Economics and Statistics,* 86(1), pp.4-29.

Jang, H.(2021). "The Credit Guarantee Effect Analysis According to the Company Year," *Journal of SME Finance,* 41(2), pp.25-50.

Kang, S., Kim, J. M., and Yoon, H. D.(2020). "Empirical Study on the Characteristics and Determinants of High-Growth Technology-Based Small and Medium-Sized Enterprises," *The Credit Card Review,* 14(2), pp.38-66.

Kim, D. H.(2016). "The Analysis of the Effect of the Job Creation and Investment Tax Credit on Employment," *Regional Industry Review,* 39 (3), pp.113-142.

Kim, H. and Kim, K.(2024). "Effect of Support of Account Receivable Insurance for Small and Medium Enterprises: Focusing on the Impact on Corporate Insolvency and Jobs," *Journal of SME Finance,* 44(4), pp.3-29.

Kim, J. R., Kim, S. B., and Nam, J. H.(2014). "The Performance Measurement of Credit Guarantee and Methods of Improvement of Its System," *Korea Review of Applied Economics,* 16(2), pp.33-64.

Kim, N., Kim, D., and Joo, Y.(2022). "A Study on the Growth of Technology-Based SMEs," *Journal of SME Finance,* 42(3), pp.29-67.

Kim, N. and Bae, J.(2024). "Effects of Entrepreneurship Education on Enterprise Performance: Mediating Effects of Entrepreneurial Self-Efficacy, Entrepreneurial Fear of Failure, and Entrepreneurial Satisfaction, and Moderating Effects of the Start-up Period," *Korean Management Review,* 53(5), pp.1227-1253.

Kim, S. B. and Kim, J. R.(2013). "A Study on the Performance Measurement of Credit Guarantee," *Industrial Economics Research,* 26(3), pp. 1381-1399.

Kim, S., Hong, J., and Lee, H.(2023). "Impacts of Government R&D Support on SMEs' Performances: Comparative Analysis Between SMEs with vs. Without Government R&D Support," *Korean Management Review,* 52 (4), pp.835-862.

Lee, J. W.(2022). "Financial Performance of Innovation-Certified SMEs and General SMEs: A Comparative Analysis," *Journal of the Korean Production and Operations Management Society,* 33(1), pp.21-39.

Lee, M., Yi, Y., and Jung, N.(2023). "The Effect of Innovation Orientation on the Performance of SMEs: Focusing on the Role of Business Model Innovation and Environmental Turbulence," *Korean Management Review,* 52 (1), pp.191-216.

Lee, S. C.(2024). "The Impact of Government Research and Development Support on Corporate Financial Performance," *Technology Management,* 9(2), pp.81-100.

Noh, Y. H.(2021). "Abolition of Joint-Liability Lending and the Operation Performance of Public Credit Guarantee," *Journal of SME Finance,* 41(1), pp.1-26.

Noh, Y.(2022). "Survival Analysis of Start-Ups Using SME Policy," *Journal of SME Finance,* 42 (2), pp.29-54.

Oh, M. H., Jung, N. K., and Lee, C. S.(2020). "Analysis on the Effects of Online-Export Supports for SMEs," *Journal of Economics Studies,* 38(4), pp.215-235.

Pearl, J.(2009), *Causality: Models, Reasoning, and Inference,* Cambridge University Press, New York, 2nd edition.

Rosenbaum, P. R.(2002), *Observational Studies,* Springer, New York, 2nd edition.

Rosenbaum, P. R. and Rubin, D. B.(1983). "The Central Role of the Propensity Score in Observational Studies for Causal Effects," *Biometrika,* 70(1), pp.41-55.

Rassen, J. A., Shelat, A. A., Myers, J., Glynn, R. J., Rothman, K. J., and Schneeweiss, S. (2012). "One-to-Many Propensity Score Matching in Cohort Studies," *Pharmacoepidemiology and Drug Safety,* 21, pp.69-80.

Roh, B. and Lee, C.(2023). "Analysis of the Effectiveness of the National Employment Support System: Examining Its Impact on Youth Job Preparation," *The Journal of Korean Policy Studies,* 23(2), pp.109-126.

Roth, J., Sant'Anna, P. H. C., Bilinski, A., and Poe, J.(2022). "What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature," *Journal of Econometrics,* 235(2), pp.2218-2244.

Rubin, D. B.(2006), *Matched Sampling for Causal Effects,* Cambridge University Press.

Shin, G. and Lee, H.(2024). "A Study on Heterogeneous Policy Effects Based on Propensity Score Quartiles," *Journal of Technology Innovation,* 32(2), pp.1-24.

Smith, J. A. and Todd, P. E.(2005). "Does Matching

Overcome LaLonde's Critique of Nonexperimental Estimators?," *Journal of Econometrics,* 125(1-2), pp.305-353.

Son, Y. H.(2008). "Consideration About the Policy and Policy Money of Small and Medium-Sized Enterprises," *Business Law Review,* 22(3), pp.377-411.

Stuart, E. A.(2010). "Matching Methods for Causal Inference: A Review and a Look Forward," *Statistical Science,* 25(1), pp.1-21.

Wooldridge, J. M.(2010), *Econometric Analysis of Cross Section and Panel Data,* MIT Press, 2nd edition.

Yoon, S., Yu, J., and Ko, H.(2022). "Work-Life Balance and Corporate Financial Performance: Focusing on the Family-Friendly Certification System," *Korean Business Education Review,* 37(6), pp.59-82.

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〈Appendix〉

A Organizational Background and Program Details

1. Korea Credit Guarantee Fund: Historical Background and Functions

The Korea Credit Guarantee Fund (KODIT) was established in June 1976 under the Korea Credit Guarantee Fund Act as a special corporation with the purpose of facilitating corporate financing by guaranteeing debts of companies with weak collateral capacity, thereby contributing to the establishment of sound credit order and balanced national economic development. As a key component of Korea's SME support infrastructure, KODIT addresses market failures in SME financing through various guarantee services.

〈Table A.1〉 Major Functions of Korea Credit Guarantee Fund

Function Category	Function Description
Credit Guarantee	General guarantee services providing guarantees for various debts that SMEs with weak collateral capacity bear to financial institutions
Securitization Guarantee	Guarantee services for securitized securities issued based on securitized assets of SPCs (Special Purpose Companies)
Company Guarantee-linked Investment	Investment services acquiring securities of companies with established credit guarantee relationships
Comprehensive Credit Information Management	Services for systematically collecting, analyzing, managing, and providing corporate credit information
Credit Insurance (Accounts Receivable Insurance)	Services to prevent chain bankruptcies by compensating for losses due to uncollectible accounts receivable (bills and trade receivables) of SMEs
Industrial Infrastructure Credit Guarantee	Guarantee services for project financing for industrial infrastructure construction
Corporate Consulting	Services providing consulting for SMEs including management diagnosis, technology evaluation, and restructuring
Startup Company Support	Guarantee support for startup companies and customized support by growth stage

2. Value-up Program: Detailed Components and Support Mechanisms

The Value-up Program, introduced in 2019, is defined as "a recovery support program to enhance continuing enterprise value and prevent insolvency by providing solutions necessary for corporate improvement led by the Korea Credit Guarantee Fund for SMEs with growth potential but temporarily vulnerable management conditions."

The main support content of the Value-up Program consists of the following elements:

(1) **Management Diagnosis and Consulting Provision**: Experts comprehensively diagnose companies' financial status, management structure, and business models and present customized improvement plans.
(2) **Financial Structure Improvement Support**: Through guarantee fee and interest rate adjustments and new funding support, it helps reduce companies' financial burden and secure liquidity.
(3) **Business Structure Reorganization Support**: It improves companies' business structure through elimination of low-profitability business divisions, strengthening core competencies, and discovering new businesses.

〈Table A.2〉 Comparison of Value-up (I) and Value-up (II) Programs

Category	Value-up (I)	Value-up (II)
Support Entity	KODIT only	KODIT + Partner banks jointly
Target Companies	KODIT claims 30% or more	KODIT + Partner banks combined claims over 50%
Partner Banks		IBK, Nonghyup Bank, Hana Bank
Common Support Content • External expert consulting		
KODIT Support	• New guarantees, preferential guarantee fees • Full maturity extension • Up to 2.0%p interest rate reduction for new guaranteed loans	
Partner Bank Support		• 0.5%p-2.0%p interest rate reduction for existing loans • Waiver of prepayment penalties and other fees • Full maturity extension
Procedural Complexity	Relatively simple	Additional procedures such as partner bank recommendation letters

As of 2021, partner banks participating in the Value-up (II) Program include Industrial Bank of Korea (agreement signed August 2019), Nonghyup Bank (August 2020), and Hana Bank (November 2020). The distinction between Value-up (I) and (II) programs reflects different levels of financial institution involvement and support intensity, which may lead to heterogeneous treatment effects in the empirical analysis.