HONG KONG MONETARY AUTHORITY

Research Memorandum 04/2024

13 March 2024

ASSESSING THE EFFECTIVENESS OF SME FINANCING GUARANTEE SCHEME USING GRANULAR DATA*

Key points

- *This research investigates the effectiveness of the Hong Kong SME Financing Guarantee Scheme (SFGS) in facilitating access to credit for small and medium-sized enterprises (SMEs). By utilising granular data from the HKMA's Granular Data Reporting (GDR) program and a deep neural network (DNN) model, the study provides an in-depth analysis of the factors influencing banks' lending behaviour towards SMEs.*

- *The results demonstrate that the SFGS has a significant impact on loan amounts, with other key determinants including collateral arrangements, reporting bank, economic sector, and loan purpose. The analysis also highlights the varying levels of credit uplift brought about by the SFGS across different industries and loan purposes, indicating that* ***the scheme is particularly beneficial for businesses in more vulnerable sectors or those seeking loans for uncertain purposes during the pandemic.*** *At the same time, the program has enhanced credit access even for borrowers with significant collateral. In addition to examining loan amounts, the study delves into the impact of the SFGS on banks' decisions to downgrade loans. We found that the presence of SFGS significantly reduces the probability of loan downgrades by 6 percentage points, providing evidence that the scheme has a stabilising effect on the perceived creditworthiness of the borrowers.*

- *In conclusion, the SFGS has effectively supported SMEs in securing financing, especially amidst the challenging period of the pandemic.* ***The findings of this research offer valuable insights for policymakers and stakeholders, underscoring guarantee schemes' vital role in spurring credit access and fostering inclusive finance to SMEs****. Nevertheless, it is important to recognise that the study's findings are based on a DNN model and may not capture the full complexity of the lending process. Future research could explore additional methodologies and data sources to further evaluate the SFGS's effectiveness and the impact of similar schemes on SME financing.*

Prepared by: *Maggie Poon, Oscar So and Max Kwong*
Economic Research Division, Research Department
Hong Kong Monetary Authority

* The authors thank Lillian Cheung, Michael Cheng, Paul Luk and Matthew Kwok for the valuable comments.

I. INTRODUCTION

The SME Financing Guarantee Scheme (SFGS) was launched in 2011 by the Hong Kong Mortgage Corporation Limited (HKMC) to assist small and medium-sized enterprises (SMEs) and non-listed enterprises in obtaining financing from participating lenders. After being transferred to the HKMC Insurance Limited in 2018, the SFGS has introduced time-limited guarantee coverage products, such as the 90% guarantee coverage scheme, and the special 100% loan guarantee scheme, to adapt to the ever-changing global economic landscape and the pandemic.

Specifically, following approval from the Legislative Council Finance Committee, the 90% Guarantee Product was launched in December 2019, with the goal of helping enterprises with limited operating experience in obtaining financing. In addition, the Financial Secretary announced a Special 100% Loan Guarantee in the 2020-21 Budget Speech, which fully guarantees loans at a discounted interest rate to aid enterprises in covering salaries, rents, and other expenses during decreased income. As of February 2024, over 11,000 and 65,000 applications had been approved under the 90% and Special 100% Loan Guarantee schemes respectively, with the aggregate facility amount totalling over HK$20 billion and HK$140 billion.

In theory, the SME financing guarantee scheme provides guarantees to banks for lending to SMEs, which should decrease the risk for banks and encourages them to continue lending to SMEs during the pandemic. With more available credit and lower interest rates, SMEs should be able to access the necessary financing to sustain their businesses, pay wages, and cover operating expenses. This should help relieve the severe funding pressures many SMEs face due to declining revenues or cash flows during the economic fallout from the pandemic.

While the scheme has gained popularity, there is limited granular evidence on the effectiveness of its enhancements. To fill this knowledge gap, our study scrutinises the effectiveness of SFGS enhancements for Hong Kong SMEs, specifically focusing on additional credit afforded to individual loans and its impact on loan classification. To achieve this objective, the study will leverage granular data from the HKMA Granular Data Reporting (GDR) scheme and apply a deep neural network (DNN) model[1] to identify the factors

---

[1] A DNN model is like a complex calculator that has three main parts: the input, the middle, and the output. Each part has lots of small parts, called "neurons," which do math operations on the input data and pass it along to the next part. The middle part of the DNN is hidden, and each neuron there does a

influencing banks' decisions. With the trained DNN model, we perform scenario analyses to estimate hypothetical SME loan amounts with and without the SFGS's presence, allowing us to evaluate the benefits derived from the SFGS. Additionally, we will examine how the SFGS influences banks' decisions to downgrade the classification of loans. Our findings can serve as a valuable reference for policymakers and stakeholders seeking to implement supportive measures for Hong Kong's SMEs.

II. LITERATURE REVIEW

While our previous studies have explored the impact of the SFGS on banks' lending behaviors at the bank level, none have examined the scheme's effect on individual loan characteristics (i.e. loan level) to the best of the author's knowledge. For instance, Tan et al. (2019) analysed the SFGS's impact on the supply of SME loans by banks in Hong Kong following the global financial crisis. Utilising a difference-in-differences model, they studied regulatory banking returns submitted to the HKMA by banks, discovering that public sector loan guarantee schemes significantly mitigated funding difficulties faced by SMEs. More recently, Wong et al. (2022) demonstrated that banks with higher exposure to the SFGS experienced greater year-on-year growth in loans to hard-hit sectors compared to other banks during the post-pandemic period, using aggregate data obtained from banking returns.

This study aims to bridge this gap in the literature by using granular corporate loan data collected under the HKMA's Granular Data Reporting (GDR) program. By analysing individual loan characteristics, the study seeks to provide insights into the SFGS's effectiveness in promoting credit access and fostering inclusive finance.

III. DATA AND METHODOLOGY

The GDR program requires pilot authorized institutions (AIs) to submit transaction-level data on corporate loans to the HKMA on a monthly basis. This enables us to carry a comprehensive, bottom-up analysis of the scheme's effect on banking behaviour. The dataset includes information on over 330,000

---

special type of math called an "activation function." This type of math helps the DNN find more complicated patterns in the data. The output part is where the final answer comes out, based on what the middle part figured out. The type of math used in the output part depends on what kind of answer we want. The strength of the signal between the neurons is determined by the "weights" or connections between them. The neurons in the hidden part apply an activation function to the weighted sum of their inputs, introducing nonlinearity into the model and allowing it to capture complex relationships between input and output variables. For details, please refer to Appendix I outstanding corporate loans, totalling HK$6 trillion (around 90% of the outstanding amount of corporate loans in Hong Kong) as of December 2023.

While this study concentrates on a specific subset of the GDR data, the sample size remains huge and poses considerable challenges to traditional econometric approaches.[2] To address this issue, this study uses deep learning techniques that offer several advantages over conventional linear regression models. In particular, deep learning algorithms are more flexible in discerning nonlinear relationships between variables, allowing for identification of complex patterns in data that models like Ordinary Least Squares (OLS) may fail to recognise. Moreover, deep learning models can derive higher-level features from raw data, including interactions among variables, enabling more accurate predictions without requiring a knowledge of the relevant features in advance.

By harnessing granular data and deep learning models, the current study seeks to provide a comprehensive evaluation of the SFGS's effectiveness in mitigating SMEs' funding stress. To accomplish this goal, the study will develop a DNN model. The construction of a DNN model entails several sequential phases, including data preprocessing, model training and validation, and performance evaluation (see Appendix II).

The features employed in our model encompass various aspects, such as collateral arrangements, borrower's economic sector, loan purpose, loan term, identity of reporting banks, and macroeconomic factors. For a complete list of variables used for constructing the model, please refer to Appendix III.[3]

As DNN models employ complex, nonlinear functions and weightings, the predictions of DNN models are usually difficult to interpret intuitively compared to simpler linear models like OLS regression. As a result, it can be difficult for humans to comprehend how DNN models produce predictions by inspecting their parameters alone, which gives rise to the so-called "black box" problem. To overcome this problem, this study will employ reverse engineering tools to gain a deeper understanding of the decision-making process of the DNN model. Specifically, by analysing the impact of removing a given variable on the model's performance while keeping all other factors constant, we can ascertain

[2] This study specifically concentrates on loans granted to borrowers who are not affiliated with mega corporates, as per the definition given in the HKMA's "Quarterly Survey: Exposures to Mega Corporates," and the loan amounts are capped at HK$18 million, which is the maximum facility amount covered by the HKMC's 80% guarantee scheme. Our sample comprises 1,409,443 distinct SME loans that were reported between April 2019 and January 2023, a period that mostly overlapped with the pandemic. Roughly 3% of these SME loans, or 42,283 observations, were insured under the SFGS.
[3] Due to data quality constraints, certain data fields are excluded in this study.

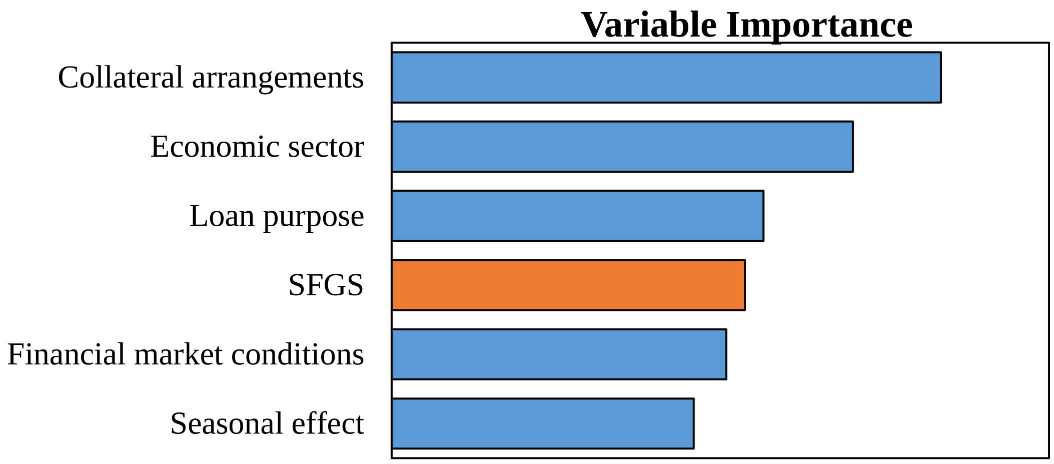
the relative importance of each variable and identify critical factors that can influence the loan amounts granted by banks to SMEs, as well as banks' decision to downgrade loans.

Lastly, the study will utilise the trained DNN model to conduct a scenario analysis, which involves estimating the hypothetical SME loan amounts both with and without the scheme. By performing this analysis, the study aims to determine the impact of the SFGS on SME loan amounts and, ultimately, assess the benefits that result from its implementation. Furthermore, the analysis will extend to examining the SFGS's effect on the likelihood of SME loan downgrades, offering deeper insights into the scheme's role in enhancing the creditworthiness and financial resilience of SMEs in the face of economic challenges.

IV. EMPIRICAL RESULTS

(i) Which factors influence the loan amounts the most?

Chart 1: Contribution of variables to loan amount predictions



Sources: GDR & staff estimations

Chart 1 highlights some of the most influential factors on the model's predictions for loan amounts. They include:

i. **Collateral arrangements**: The provision of collateral emerges as the most crucial determinant of loan amount. This outcome is consistent with expectations since collateral significantly reduces the credit risk faced by lenders. Collateral serves as a safeguard that banks can liquidate to recover a portion or the entirety of the loan amount if a borrower defaults. Consequently, lenders are more likely to offer larger loan amounts to borrowers who provide collateral, minimising their exposure to potential losses.

ii. **Economic sector**: Different industries have varying capital requirements and risk levels, which directly impact loan sizes. Capital-intensive sectors, like manufacturing, may require larger loans for equipment or infrastructure, while service-based industries may need smaller loans for operating expenses. Additionally, banks may exercise caution when lending to sectors prone to economic volatility, leading to diverse loan sizes across sectors.

iii. **Loan purpose**: The intended use of a loan significantly impacts its size. For example, loans for long-term investments, such as expanding operations, may be more appealing to lenders since they contribute to the growth of business. Conversely, the size of loans for short-term needs, like working capital or cash flow management, may be smaller as they address temporary liquidity challenges and therefore may be deemed riskier to lenders.

iv. **SFGS**: Although not as influential as the other factors, our model shows that the SFGS still notably impacts loan amounts. The SFGS's effectiveness in reducing lenders' credit risk when lending to vulnerable borrowers is unsurprising. By guaranteeing part of the loan, the SFGS encourages lenders to lend to individuals or businesses that may otherwise be deemed too risky to qualify for a larger loan.

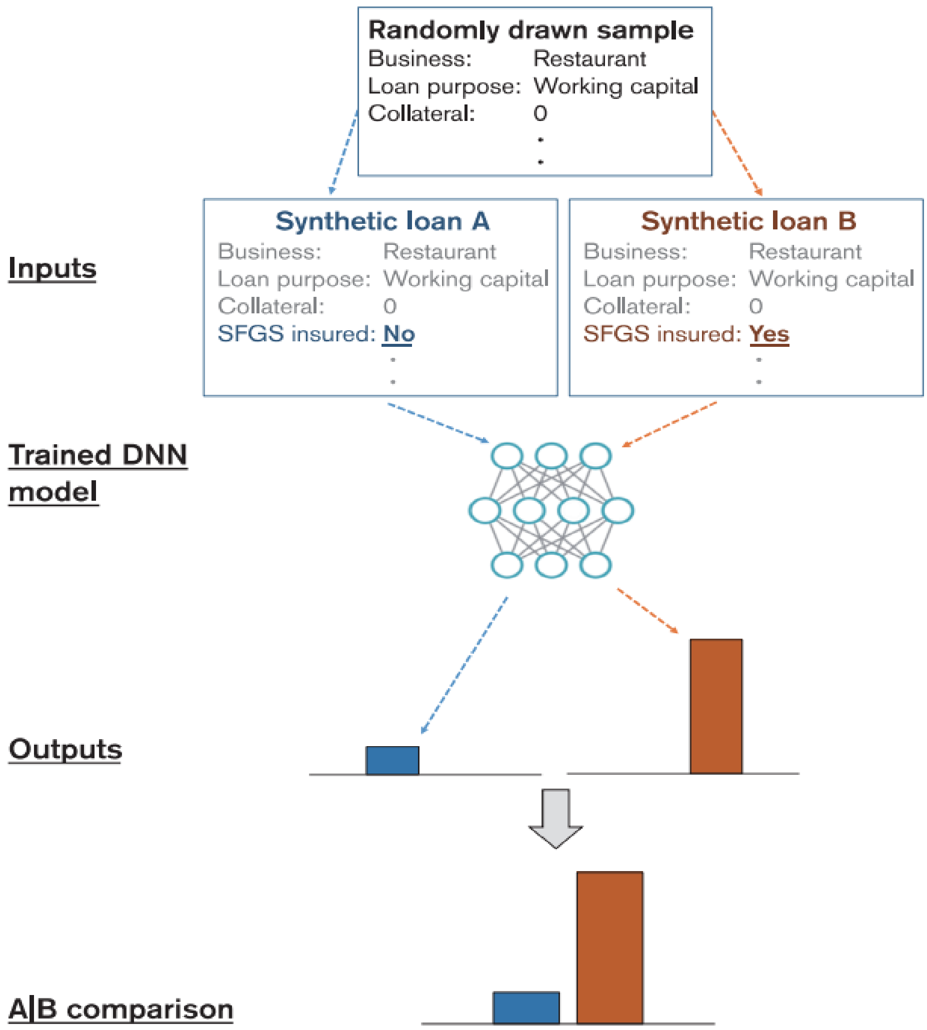
(ii) How substantial is the impact of SFGS on the size of loan to SME borrowers?

Our findings suggest that the SFGS plays a significant role in influencing the size of loan extended to SME borrowers, which raises the question of how substantial its impact is. However, it is crucial to recognise that the impact of the program is not uniform across all loans, as various factors such as loan purposes or the industries borrowers operate in can influence the scheme's benefits. Therefore, without setting the proper context, our model cannot provide a definitive answer regarding how substantial the SFGS's impact is.

To explore the SFGS's effect quantitatively, we conducted a hypothetical scenario analysis using our trained DNN model (Chart 2). More specifically, we randomly selected a data point from our sample and generated two SME loans with identical attributes.[4] We then artificially modified a single characteristic of the loans, namely the SFGS coverage status, while holding all other things constant. By comparing how this change in the SFGS coverage status would affect our model's prediction, we can infer the effect of the SFGS on the loan amount. This approach simulates an experimental setting and mitigates endogeneity concerns regarding firm characteristics that systematically determine access to SFGS and loan amounts.

In the following section, we put forth hypothetical loan amount estimates for three illustrative SME loans—a working capital loan for a restaurant industry borrower, a working capital loan for an exporter, and a trade financing loan for an exporter—under circumstances with and without the SFGS program.

Chart 2: Graphical illustration of scenario analysis



[4] To verify the reliability of our results, we conducted several additional trials using distinct, randomly selected subsets of the data. These repetitions of the analysis yielded consistent findings.

i. Working capital loan in the restaurant industry

The DNN model's analysis revealed that without the SFGS, the hypothetical loan amount for the restaurant industry borrower would be HKD 197,000 (Chart 3). With the program, the loan amount would increase substantially to HKD 943,000. This massive credit uplift of HKD 746,000 (378%) highlights the program's positive impact on the restaurant sector. The substantial increase in this scenario can be attributed to the heightened risk associated with the pandemic in the restaurant industry, which has faced closures, reduced capacity, and shifting consumer habits. Lenders may be more hesitant to extend credit without the financial security provided by the SFGS.

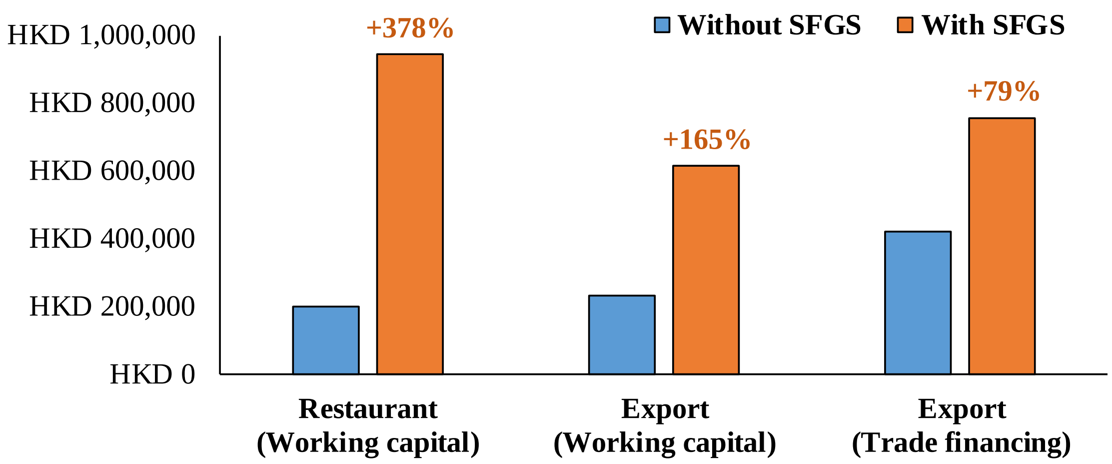
ii. Working capital loan in the export industry

In the export industry, the DNN model estimated a hypothetical loan amount of HKD 232,000 without the SFGS in place. With the program, the loan amount would increase modestly to HKD 615,000, resulting in a credit uplift of HKD 383,000 (165%). Although the export industry was not as severely impacted as the restaurant industry during the pandemic, it still faced various challenges such as supply chain disruption, geopolitical tensions, and the potential for trade disputes that made lenders more cautious about extending credit without the safety net provided by the SFGS.

iii. Trade financing loan in the export industry

If the loan purpose changes from working capital to trade financing, the DNN model estimated a hypothetical loan amount of HKD 422,000 without the SFGS in place. In contrast, with the program, the loan amount would increase to HKD 758,000, resulting in a credit uplift of HKD 336,000 (79%).

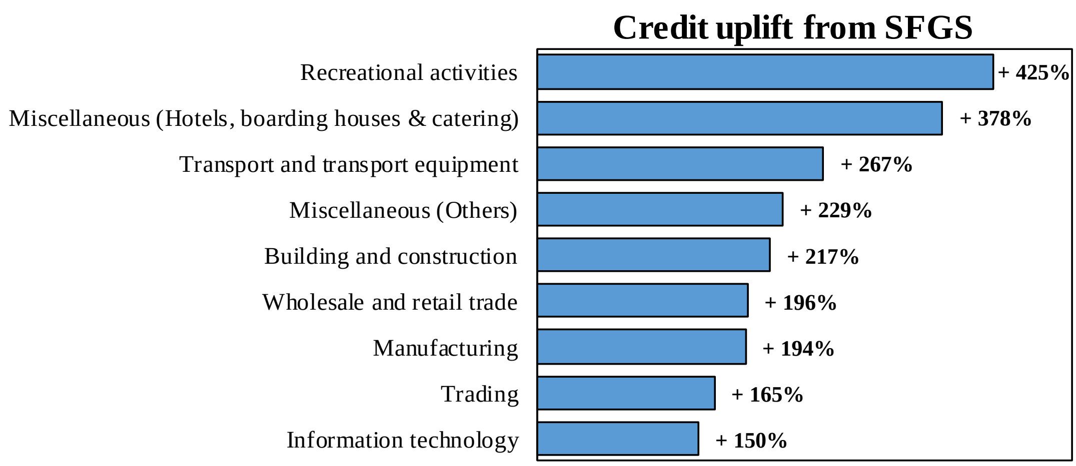
Chart 3: Impacts of SFGS on SME loan amounts (case study)



Sources: GDR & staff estimations

The scenario analysis demonstrates that the credit uplift provided by the SFGS program varies significantly across different industries and loan purposes (Chart 3). To further analyse and extend these findings, additional hypothetical scenarios were evaluated. Controlling for other loan and borrower characteristics, estimated loan amounts were calculated with and without the SFGS program for all major industry sectors and loan purposes. This comprehensive approach enables a holistic understanding of how the SFGS's benefits differ across sectors and purposes.

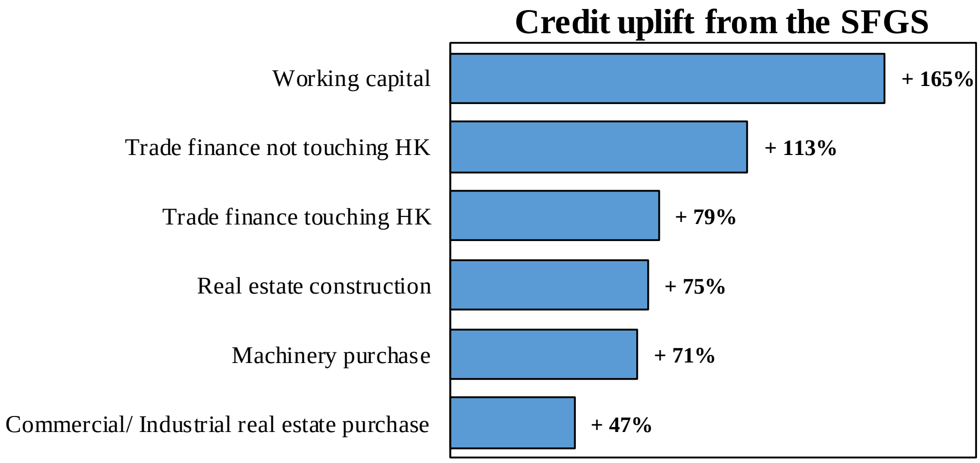
Chart 4: Impacts of SFGS on SME loan amounts (by sector)



Sources: GDR & staff estimations

Chart 4 shows how the impact of the SFGS varied across major industry sectors. As expected, the SFGS can provide relatively more credit support to those industries that were hardest hit by the pandemic, such as recreation, hospitality, and food services. In contrast, the SFGS can provide relatively modest but still significant support to industries that were more stable and less affected, such as manufacturing.

Chart 5: Impacts of SFGS on SME loan amounts (by loan purposes)

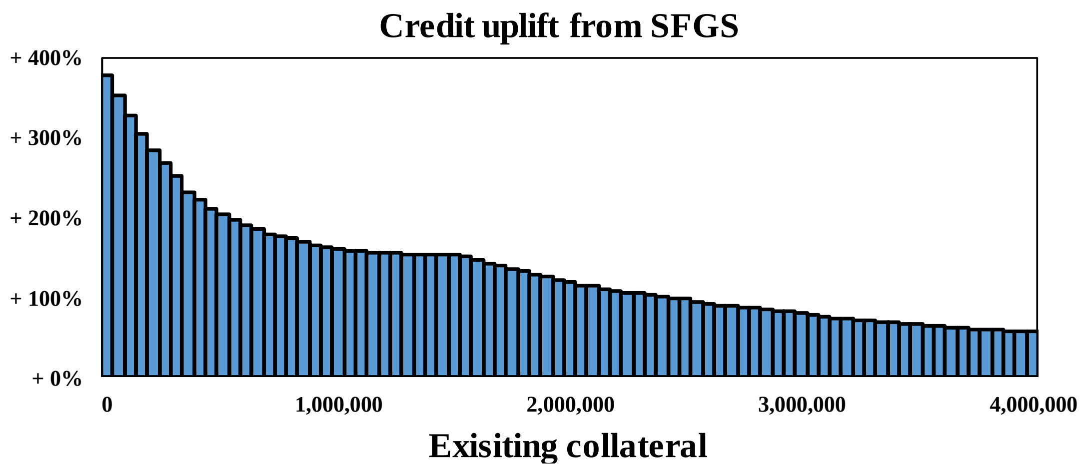


Sources: GDR & staff estimations

Chart 5 displays a similar pattern across loan purposes. The SFGS is estimated to provide the greatest support for working capital loans, while loans for equipment or real estate purchases see more limited benefits. This disparity suggests lenders view uncertainty and risk as more significant for cash flow-related expenses than for those with collateral values.

Apart from economic sector and loan purpose, the amount of collateral available is another key factor influencing the impact of the SFGS, as shown in Chart 1. Chart 6 demonstrates the relationship between the magnitude of the uplift from the SFGS and the amount of existing collateral. While loans with greater collateral tend to receive smaller benefits from the program, the SFGS has nonetheless provided meaningful relief even to borrowers with substantial collateral. This indicates that the SFGS has effectively increased access to credit for a diverse range of borrowers.

Chart 6: Impacts of SFGS on SME loan amounts (by collateral amount)



(iii) Does SFGS affect banks' loan downgrade decisions?

The preliminary findings suggest that banks are more inclined to offer larger credit amounts to borrowers under the SFGS. This raises an intriguing question: Does the SFGS also impact how banks classify loans, particularly when it comes to downgrading a loan's classification? [5]

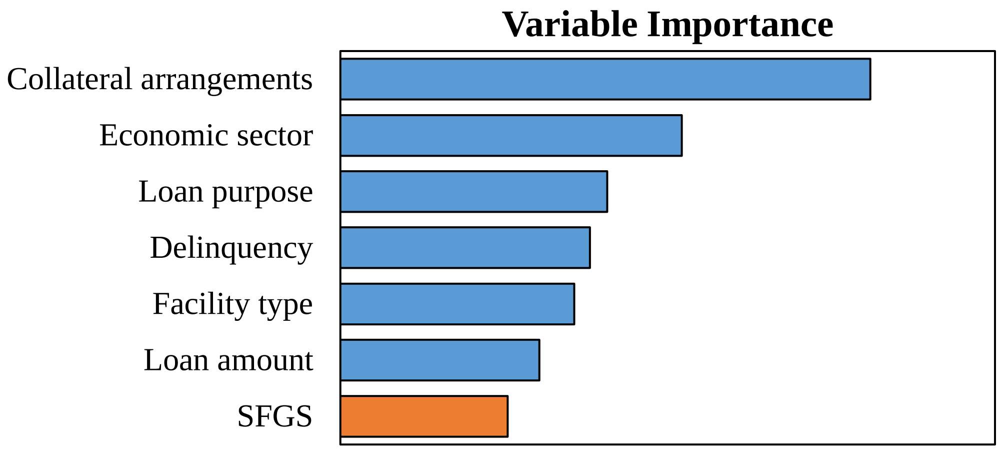
To answer this question, we developed a DNN model to predict the probability of a loan being downgraded within the next three-month period. This approach enables us to delve deeper into the possible implications of the SFGS on banks' loan classification decisions.

Under the HKMA loan classification, loans are categorised into five groups based on the borrowers' repayment ability and the level of uncertainty surrounding the recovery of loan principal and interest. These groups include: (i) Pass, (ii) Special Mention, (iii) Substandard, (iv) Doubtful, and (v) Loss, each indicating a progressive level of concern regarding repayment. In our study, we tailored a DNN to forecast the probability of a loan's status being downgraded within an upcoming three-month window, factoring in various loan attributes, including the presence of SFGS protection.

By applying the reverse engineering technique mentioned earlier, we were able to decode our DNN and identify the key determinants influencing the model's predictions, as illustrated in Chart 7.

Chart 7: Contribution of variables to loan downgrade predictions

[5] To improve the robustness of our analysis and ensure an adequate number of positive observations, we have broadened our sample to include loans with both 80% and 90% SFGS coverage.



Sources: GDR & staff estimations

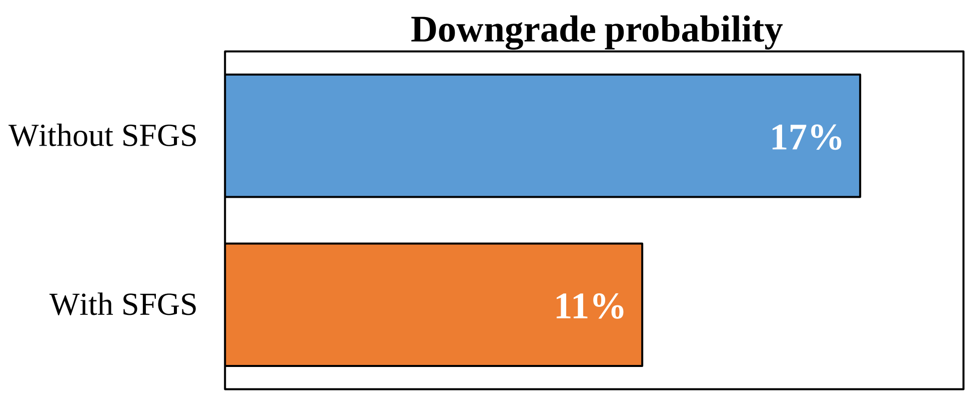
The analysis presented in Chart 7 reaffirms our earlier findings, with collateral arrangements emerging as the most influential determinant in the AI's classification decisions regarding loan downgrades. This finding is unsurprising as collateral serves as a critical security measure for banks, offering a form of protection should a borrower fail to meet the repayment obligations. The presence of collateral significantly reduces the perceived risk, which in turn may influence a bank's decision when it comes to classifying a loan's recoverability.

Not far behind in significance are factors such as the economic sector in which the borrower operates, the purpose for which the loan was sought, the loan delinquency history, and the type of loan facility. Although less dominant compared to these factors, the SFGS still holds considerable importance within the context of loan classification, as evidenced by the results derived from our model's findings.

(iv) How substantial is the impact of SFGS on downgrade probability of loans?

Having established that the SFGS plays a significant role in influencing AIs' decisions to downgrade loans, we sought to quantify the extent to which the SFGS reduces the probability of loan downgrades. Our analysis, presented in Chart 8, shows that the scheme on average would reduce the probability of downgrading by 6 percentage points from 17% to 11%, underscoring the positive influence of the SFGS on the stability of credit provided to smaller enterprises.

Chart 8: Impacts of SFGS on loan downgrade probability



Sources: GDR & staff estimations

Overall, the findings indicate that the SFGS is particularly beneficial for firms in more vulnerable industries or those requiring loans for purposes perceived as more uncertain by lenders, such as working capital. At the same time, the program has meaningfully enhanced credit access even for borrowers with significant collateral and has a stabilising effect on the perceived creditworthiness of the borrowers.

However, it is essential to note that the above scenarios represent hypothetical examples derived from the model. The actual impact of the SME financing guarantee scheme on each loan would depend on various factors such as the duration and interest rate. Additionally, during the pandemic, there were other temporary government relief measures targeting different sectors. The analysis does not account for these parallel programs, so the estimated SFGS effects may overstate its true impact.

V. CONCLUSION

This study aimed to analyse the effectiveness of the SFGS in Hong Kong using granular data obtained from the HKMA's GDR program and a DNN model. Our findings reveal that the SFGS significantly influences loan amounts granted to SMEs and contributes to the stabilisation of the perceived creditworthiness of the borrowers.

Our results suggest that the SFGS has been effective in supporting SMEs, particularly those operating in vulnerable industries or requiring loans for purposes deemed uncertain by lenders during the pandemic. At the same time, the program has meaningfully enhanced credit access even for borrowers with significant collateral. This support has been particularly valuable during the pandemic, when businesses faced heightened uncertainty and financial challenges.

Moreover, this study extends to examine the influence of the scheme on AIs' decision to downgrade the classification of loans. Utilising a similar DNN model, we discovered that while the SFGS is less impactful than factors such as collateral arrangements or the borrower's economic sector, it nevertheless plays a role in the loan classification process. We quantified the scheme's effectiveness in reducing downgrade risks and found that the SFGS would decrease the probability of loan downgrades by 6 percentage points. This underlines the SFGS's role in stabilising the credit environment for SMEs, contributing to their financial resilience during challenging economic times.

These findings contribute to our further understanding of the impact of the SFGS on SME financing and provide insights for policymakers on the effectiveness of such guarantee schemes in promoting credit access and fostering inclusive finance. However, it is essential to note that our study only provides an approximation of the SFGS's impact based on a DNN model and may not capture the full complexity of the lending process. Future research could explore alternative methodologies and data sources to further investigate the effectiveness of the SFGS and other similar schemes in supporting SMEs.

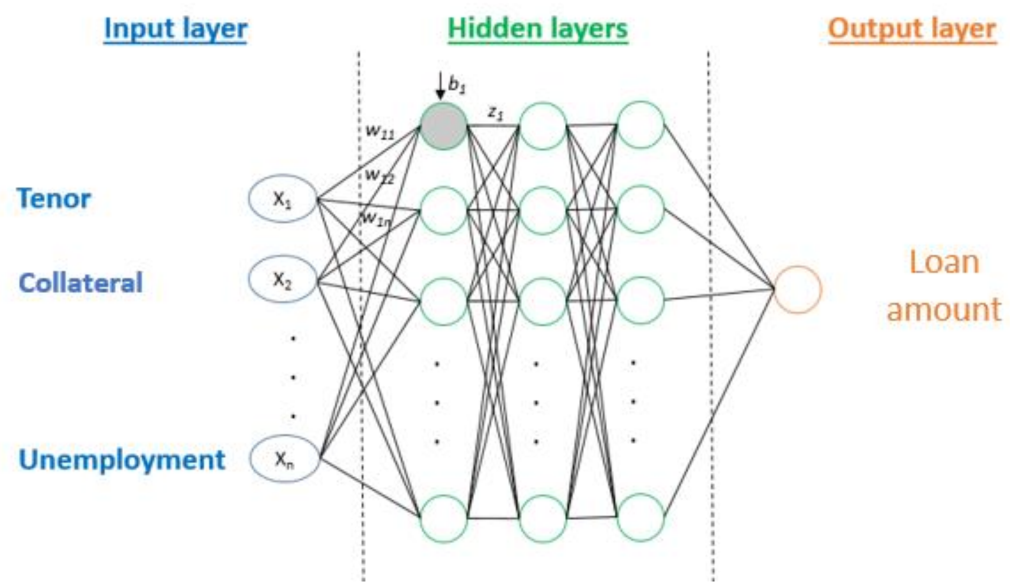
VI. REFERENCE

Tan, E., Wong, E., Ho, K. and Wong, A., (2019): "Evaluation of the Effects of Bank Regulatory Reforms and Loan Guarantee Schemes on Loans to Small and Medium-Sized Enterprises", *HKMA Research Memorandum*, No. 2019/11, The Hong Kong Monetary Authority, 18 November 2019.

Wong, E., Ho, K., Wong, A., & Lo, V. (2022). "The Effects of Covid-19 Support Measures on Bank Lending: Lessons from the Release of the Countercyclical Capital Buffer and Loan Guarantee Schemes in Hong Kong", *HKMA Research Memorandum*, No. 2022/03, The Hong Kong Monetary Authority, 2 June 2022.

VII. APPENDIX I: AN OVERVIEW OF DEEP NEURAL NETWORK MODELS

Chart A1: A graphical illustration of DNN model used in this note



A DNN structure typically consists of (i) an input layer, (ii) multiple hidden layers, and (iii) an output layer. Within each layer, there are numerous mathematical processing units (known as "**neurons**") that take in the output signal from the previous layer, and convert it into some form that can be taken as input to the next layer.

Taking the neuron shaded in Chart A1 as an example. First, it calculates a simple weighted sum (a_1) by combining (i) inputs from the preceding layers (x_1, x_2, ... x_n) and (ii) an intercept term (b_1, known as a "**bias**"):

$$a_j = \sum_{i=1}^{n} w_{ji} x_i + b_j$$

Next, it transforms the weighted sum into an output signal (z_1) using a non-linear function (known as an "**activation function**"):

$$z_j = f(a_j)$$

Such an output signal (z_1) would then be passed down as an input for neurons in the next layer of the network.

In the above example, parameters such as weights (w_{ji}) and biases (b_j) are all adjustable and their values are continuously fine-tuned by a ML algorithm during the model training stage, in order to minimise the prediction error. In general, the training time required for a given DNN model depends on its complexity, which in turn varies directly with the numbers of layers and neurons.

VIII. APPENDIX II: CONSTRUCTION OF A DNN MODEL

The construction of a DNN model entails several sequential phases:

1. Data pre-processing

The initial stage of data preprocessing involves cleaning, transforming, and normalising raw data to ensure its compatibility with subsequent model development stages. This phase includes converting categorical variables into numerical representations using one-hot encoding, eliminating missing values, and normalising data to align all features on a comparable scale.

2. Model training and validation

Analogous to how humans learn, deep learning algorithms acquire knowledge through experience by repeatedly executing a task and fine-tuning their approach to yield improved results. In this stage, the DNN model is trained on a subset of pre-processed data using an optimisation algorithm to minimise a predefined loss function. The model's parameters are adjusted iteratively throughout training to enhance predictive accuracy, while validation is performed on a separate data subset to monitor its performance and prevent overfitting.[6]

3. Performance evaluation:

Following the training and validation stages, the DNN model's performance is assessed using various metrics. These metrics offer insights into the predictive accuracy of the model and its ability to generalise to new, unseen data.

[6] To further enhance the reliability and generalisability of the model, we employed a technique called cross-validation. Cross-validation involved generating alternative versions of the DNN model by repeating the randomisation process with different random seeds. The model was trained and tested on these different sets. Notably, all versions of the model yielded similar results, indicating the model's consistency and stability.

IX. APPENDIX III: EXPLANATORY VARIABLES USED IN CONSTRUCTING THE MODEL

Category	Data field
Loan characteristics	Collateral amount (HKD equivalent)
	Loan amount at origination (HKD equivalent)
	Closing outstanding amount (HKD equivalent)
	Tenor At origination
	Reporting position date
	Specific provision
	Interest payment frequency
	Currency
	Governing law(s)
	Type of facility
	Loan use economic sector
	Recourse
	Seniority/Lien
	Counterparty type of Mainland exposure
	Syndicate indicator
	Loan purpose
	Loan use location
	SME Financing Guarantee indicator
	SME Loan Guarantee indicator
	Loan status
	HKMA loan classification
	Interest rate type
	Reference rate
	Reporting bank AI code
Macroeconomics	Unemployment rate
	Inflation rate
	PMI
	Retail sales (value)
	Retail sales (volume)
	Tourist arrivals
	Imports (value)
	Exports (value)
	Imports (yoy growth)
	Exports (yoy growth)
Financial market	Hang Seng Index