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Decomposing bank net interest margin: A dynamic stochastic frontier and dominance analysis

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Abstract

This study aims to disentangle and quantify the time-varying inefficiency component of the Net Interest Margin (NIM), separating it from other contributors such as core factors, control factors, and bank-specific heterogeneity. To achieve this, a two-step empirical design was employed, combining a dynamic stochastic frontier model with dominance analysis. The procedure was replicated across various subsamples—based on ownership structure, bank scale, and the COVID-19 period—as robustness checks. The results show that time-varying inefficiency plays the most significant role in explaining NIM, accounting for approximately 47.1%, while core factors contribute around 31.2%. Only modest variations were found across subsamples. This study offers an innovative methodological approach and concrete findings on one of the most critical banking metrics, with meaningful policy implications.

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1. Introduction

Net Interest Margin (NIM) is a critical metric in banking. Beyond its role as a measure of profitability, NIM also reflects the efficiency of financial intermediation (Demirgüç-Kunt & Huizinga, 1999; Maudos & de Guevara, 2004). This function is particularly important in many developing countries, where the banking system serves as the backbone of business financing (Dwumfour, 2019).

While a substantial body of literature examines the determinants of NIM, studies that numerically decompose NIM into its core components and inefficiency remain surprisingly scarce (Mateev et al., 2024). Numerical decomposition is of paramount importance because it offers concreteness and precision—critical inputs for crafting well-designed and effective policy interventions (Satyagraha et al., 2022). It is not sufficient to know whether a factor has a positive or negative impact on NIM; we must also understand its magnitude to devise targeted policy actions.

NIM also reflects a bank's pricing behavior under a two-step production model. Accordingly, it comprises both production cost components and (inefficient) cost excess (Horvatová, 2018 and Dzeha, 2023). Moreover, observed NIM data may not represent an optimized outcome—i.e., NIM is not always efficient.

We model NIM as linear and additive in nature, following Chambers & Fare (2004) and Agori et al. (2019). The explanatory variables include production cost components, inefficiency, and heterogeneity. This relationship can be expressed by the following equation:

$$NIM = w_{RC} Risk\ Cost + w_{OP} Operational\ Cost + w_{RR} Required\ Return + w_{IE} Inefficiency + w_H Bank\ Heterogeneity \quad 1)$$

In this framework, NIM is assumed to cover risk costs, operational costs, and the (investor) required return. Risk costs consist of liquidity risk (Angbazo, 1997) and credit risk (Hanweck & Ryu, 2005). Operational costs encompass all variable and fixed expenses necessary to run banking operations (Maudos & de Guevara, 2004). As in any business, bank investors must be adequately compensated through their required return (Fries & Taci, 2005). Under perfect information and optimal behavior, all component weights should be positive (i.e., banks able to pass these components to their customer), with their magnitudes reflecting relative importance. However, due to inefficiency, this condition may not hold.

Inefficiency may stem from factors such as managerial and technical constraints or policy response lags (Anwar, 2019; Rahman et al., 2023). Bank-level heterogeneity captures residual uniqueness that may arise from cultural or leadership differences (Chowdhury et al., 2022). Both inefficiency and heterogeneity are assumed to be unobserved and thus are estimated from the data.

We propose a novel and innovative approach that combines Stochastic Frontier Analysis (SFA) with Dominance Analysis (DA), following Luchman (2014). SFA is a widely used method for estimating inefficiency (Kumbhakar & Lovell, 2000). In the SFA framework, it is assumed that an optimized or best-practice behavior—referred to as the stochastic frontier—exists within the observed data (Aigner et al., 1977); inefficiency is then measured as the deviation from this frontier.

The version of SFA employed in this paper is the dynamic model developed by Belotti and Ilardi (2018), which is well-suited to the structure of our panel dataset. Given that NIM is heavily influenced by external shocks (Islam & Nishiyama, 2016; Nguyen et al., 2023), a dynamic modeling approach is essential. Our modeling extends the work of Bikker & Vervliet (2018). The inefficiency and heterogeneity terms are estimated through the SFA regression, and together with other components, they are used as inputs for the DA. This integrated procedure allows us to obtain a comprehensive and robust measure of inefficiency and its relative contribution to NIM.

Consistent with the earlier exposition, the decomposition of NIM is assumed to be additive, and we follow the procedure outlined by Luchman (2021).

1. Methodology and Data

Expanding from Bikker and Vervliet (2018), our dynamic SFA regression is of Autoregressive Distributed Lag type of order 4[1] that can be expressed as follows

$$NIM_{it} = \alpha_0 + \sum_{p=1}^{4} \beta_{0p} NIM_{i,t-p} + \sum_{q1=1}^{4} \beta_{1q1} NPL_{i,t-q1} + \sum_{q2=1}^{4} \beta_{2q2} LIQ_{i,t-q2} + \sum_{q3=1}^{4} \beta_{3q3} CIR_{i,t-q3} + \sum_{p3=1}^{4} \beta_{3q4} ROE_{i,t-q4} + \beta_5 CAP_{it} + \beta_6 SIZE_{it} + \varepsilon_{it} \quad 2)$$

$$\varepsilon_{it} = v_i - u_{it} \quad 3)$$

$$u_{it} \sim N(\mu_{it}, \sigma_u^2) \quad 4)$$

The variables and their proxies follow standard practices in the NIM literature (Maudos & de Guevara, 2004; Rahman et al., 2023). The outcome variable is Net Interest Margin (NIM), calculated as interest revenue minus interest cost, divided by total interest-earning assets. Both the non-performing loan ratio (NPL, a proxy for credit risk, measured as non-performing loans divided by total assets) and the liquidity ratio (LIQ, a proxy for liquidity risk, measured as liquid assets divided by total assets) represent components of risk cost. The cost-to-income ratio (CIR), calculated as non-interest expenses divided by total revenue, is used as a proxy for operational efficiency. Return on equity (ROE), defined as net profit divided by total equity, serves as a proxy for investor-required return. Capital adequacy (CAP), calculated as equity divided by total assets, and bank size (SIZE), proxied by the logarithm of total assets, are included as control variables.

Equation 3 specifies that the composite error term ε_{it} consists of two parts: v_i, which captures time-invariant bank-level heterogeneity, and u_{it}, which represents time-varying inefficiency. Equations 3 and 4 are estimated using a cost function-based stochastic frontier analysis (SFA), where u_{it} is assumed to follow an exponential distribution with strictly positive support.

[1] This lag is obtained from Andrew & Lu (2001) procedure. The output is available upon request.

The dataset is a long-panel type, comprising 91 Indonesian commercial banks with monthly observations from January 2012 to January 2023. Data were obtained from the financial reports published on the OJK (Financial Services Authority) website. Following Sullivan et al. (2021), winsorization was applied at the 5th and 95th percentiles to mitigate the impact of outliers.

The analysis proceeds as follows. First, descriptive statistics and unit root tests are conducted. The unit root test uses the modified Dickey-Fuller approach as recommended by Pesaran (2007). Next, a sequence of panel data regressions is performed to characterize panel heterogeneity, including Ordinary Least Squares (OLS), Fixed Effects (FE), and Random Effects (RE) models, following the framework outlined by Cameron & Trivedi (2005). Finally, the presence of autocorrelation is tested following Born and Breitung (2016), and heteroscedasticity is assessed using methods suggested by Greene (2000).

Second, we estimate Equation (1) following the procedure outlined by Belotti and Ilardi (2018) and compute the inefficiency term using the method proposed by Jondrow et al. (1982). We then apply a linear Dominance Analysis (DA) model, with NIM as the outcome variable and four components—core factors, inefficiency, control variables, and bank-specific heterogeneity—as predictors.

We assume that inefficiency is the outcome of a dynamic process, consistent with Ahn et al. (2000) and Emvalomatis (2012). Nonetheless, we model NIM decomposition as a linear relationship due to its additive nature (Chambers & Fare, 2004).

Dominance Analysis is a robust technique for assessing the relative importance of predictors in multiple regression models. Unlike traditional methods that rely solely on standardized coefficients or p-values, DA systematically evaluates the incremental contribution of each predictor across all possible subset models (Luchman, 2014). This feature makes it particularly suitable for contexts involving multicollinearity, such as ours. We follow the procedure outlined by Luchman (2021).

Lastly, we replicate all previously explained steps using subsamples (OWNER/SCALE/COVID) for robustness check. There are three categories of OWNER (Foreign-FOR, Government-GOV and Private-PRIV); two categories of SCALE (Big-medium bank-BIGMED and Small). Covid category is set as PER<2020m3=0; PRECOVID; PER≥2020m3=0; COVID. The cut off 2020m3 is taken from the Ministry of Health declaration of COVID as pandemic. We refrain from estimating bank specific heterogeneity in subsamples[2].

3. Results and Discussion

Table 1 reports the descriptive statistics. The data appear to be well-behaved, with characteristics consistent with recent studies on Indonesian banks (see, for example, Chowdhury et al., 2022; Modjo & Giannina, 2024; Ariefianto et al., 2024). As shown in the lower part of the table, all variables used in the analysis are stationary, supporting the appropriateness of our SFA setup.

[2] Estimation of bank specific heterogeneity resulted in negative value of DA share statistic which is logically implausible. Also, we combine following subsamples Big Bank and Medium Bank into Big Med since Big Bank only has 6 banks.

Table 1. Descriptive Statistics. This table reports descriptive statistics of variables used in the study.

Stats	NIM	NPL	LIQ	CIR	ROE	CAP	SIZE
Mean	0.049	0.028	0.182	0.397	0.067	0.266	6.613
p50	0.041	0.024	0.162	0.303	0.038	0.203	6.548
SD	0.037	0.020	0.088	0.294	0.076	0.153	0.755
Min	0.006	0.001	0.067	0.025	-0.005	0.115	4.991
Max	0.141	0.076	0.389	1.230	0.280	0.661	9.628
p5	0.006	0.001	0.067	0.067	-0.005	0.115	5.424
p95	0.141	0.076	0.389	0.992	0.280	0.661	7.974
Unit Root	-11.62***	-1.89**	-11.129***	-9.83***	-10.131***	-2.91***	-3.878***
N	12103	12103	12103	12103	12103	12103	12103

The sequence of panel regressions (see Table 2) indicates that the linear relationship between NIM and the regressors is best captured by the Fixed Effects (FE) model. All explanatory variables—both core and control—are highly significant. Banks appear to successfully pass on credit risk (NPL) and required return (ROE) into NIM pricing, consistent with findings by Fries & Taci (2005) and Bikker & Vervliet (2018). In contrast, LIQ and CIR enter the equation with negative and highly significant coefficients, suggesting that banks fail to incorporate these components into NIM mark-up pricing (Angori et al., 2019; Nguyen et al., 2020). The regression results also indicate the presence of serial correlation and heteroscedasticity. To address these issues, the SFA estimation incorporates robust standard error corrections.

Table 2. Standard Panel. This table reports standard panel regressions (OLS, FE and RE) with NIM as dependent variables. Standard errors in parentheses. The significance levels at 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.

VARIABLES	OLS	2WAY-FE	RE
NPL	0.209***	0.138***	0.165***
	(0.00931)	(0.00915)	(0.0122)
LIQ	-0.0333***	-0.0442***	-0.0423***
	(0.00223)	(0.00220)	(0.00298)
CIR	-0.0274***	-0.0102***	-0.0290***
	(0.000701)	(0.000811)	(0.00106)
ROE	0.397***	0.243***	0.423***
	(0.00249)	(0.00306)	(0.00290)
CAP	0.0630***	0.0291***	0.0595***
	(0.00129)	(0.00201)	(0.00236)
SIZE	-0.00108***	-0.00345***	0.000672
	(0.000288)	(0.000831)	(0.000699)
Constant	0.0244***	0.0251***	0.0155***
	(0.00197)	(0.00543)	(0.00449)
FE Test- Bank		27.7***	
Period		325.64***	
RE Test			194.81***
Hausman		27.71***	
Auto Corr.		63.299***	
Hetero		79.776***	
R-squared	0.695	0.8734	
Number of Bank	91	91	91
Number of BANK	12103	12103	12103

A strong dynamic pattern is particularly evident for NIM, NPL, LIQ, and ROE (see Table 3). The lower part of Table 3 highlights the high statistical significance of sigma-u, sigma-v, and their ratio (lambda) across both the full sample and subsamples. Collectively, these statistics indicate that time-varying variance (the inefficiency term) is significant and plays a more substantial role than residual heterogeneity. This evidence provides strong empirical support for the validity of our SFA model.

Table 3. SFA Regressions. This table reports SFA regressions with NIM as dependent variables. Standard errors in parentheses. The significance levels at 0.01, 0.05, and 0.1 are denoted by ***, **, and *, respectively.

VARIABLES	FULL	FOR	GOV	PRIV	BIG-MED	SMALL	NONCOVID	COVID
L.NIM	-0.0793***	-0.100***	0.101**	-0.0843***	-0.111***	-0.0677***	-0.134***	0.274***
	(0.0132)	(0.0387)	(0.0394)	(0.0315)	(0.0272)	(0.0161)	(0.0210)	(0.0366)
L2.NIM	-0.0855***	-0.0436	-0.0884***	-0.0772*	-0.0796***	-0.0882***	-0.134***	-0.0871***
	(0.0121)	(0.0498)	(0.0298)	(0.0443)	(0.0221)	(0.0151)	(0.0120)	(0.0205)
L3.NIM	-0.102***	-0.0537*	-0.326***	-0.0681	-0.125***	-0.0934***	-0.141***	-0.454***
	(0.0213)	(0.0300)	(0.0206)	(0.0596)	(0.0339)	(0.0293)	(0.0112)	(0.0255)
L4.NIM	0.0835***	0.109**	0.0428	0.0980***	0.0600	0.0920***	-0.00316	0.120***
	(0.0207)	(0.0440)	(0.0390)	(0.0329)	(0.0382)	(0.0260)	(0.0221)	(0.0269)
L.NPL	0.0429*	0.0464	0.232***	0.00639	0.0988*	0.0289	0.0655**	0.230***
	(0.0227)	(0.0412)	(0.0741)	(0.0509)	(0.0568)	(0.0255)	(0.0260)	(0.0806)
L2.NPL	-0.0331*	-0.00290	-0.159***	-0.0164	-0.0236	-0.0369*	-0.0767***	-0.0276
	(0.0169)	(0.0203)	(0.0603)	(0.0357)	(0.0316)	(0.0214)	(0.0204)	(0.0475)
L3.NPL	0.0216	-0.0110	-0.00910	0.0250	0.0399	0.0167	0.0331*	-0.110**
	(0.0175)	(0.0309)	(0.0951)	(0.0313)	(0.0300)	(0.0204)	(0.0184)	(0.0551)
L4.NPL	0.0131	0.0159	0.144*	0.0149	0.00779	0.0175	0.0105	0.0743
	(0.0164)	(0.0432)	(0.0864)	(0.0349)	(0.0322)	(0.0180)	(0.0151)	(0.0534)
L.LIQ	-0.0225***	-0.00887	-0.133***	-0.00918	-0.0230**	-0.0214***	-0.0225***	-0.0663***
	(0.00546)	(0.00886)	(0.0137)	(0.00658)	(0.0106)	(0.00644)	(0.00514)	(0.0151)
L2.LIQ	0.0106***	0.00524	0.0399***	0.00289	0.00195	0.0125***	0.00705	0.0257**
	(0.00411)	(0.00340)	(0.0147)	(0.00561)	(0.00913)	(0.00486)	(0.00456)	(0.0116)
L3.LIQ	0.00971**	-0.00421	0.0263***	0.00436	0.0140	0.00925**	0.0112***	-0.0259**
	(0.00410)	(0.00691)	(0.0101)	(0.00585)	(0.0110)	(0.00441)	(0.00418)	(0.0126)
L4.LIQ	-0.0142***	-0.000210	0.0314**	-0.00663	-0.0138*	-0.0141***	-0.00720*	0.00219
	(0.00374)	(0.00547)	(0.0130)	(0.00534)	(0.00790)	(0.00456)	(0.00401)	(0.0113)
L.CIR	4.47e-05	-0.00170	0.000914	0.000500	-0.00158	0.000724	8.28e-05	0.00616
	(0.00139)	(0.00138)	(0.00628)	(0.00175)	(0.00182)	(0.00157)	(0.00164)	(0.00520)
L2.CIR	-0.00104	0.000796	-0.000302	0.00152	0.00111	-0.00179	-0.00173	0.00715
	(0.00195)	(0.00152)	(0.00321)	(0.00186)	(0.00171)	(0.00263)	(0.00192)	(0.00476)
L3.CIR	-0.000377	-0.00309**	-0.00293	0.00179	-0.00354*	0.00118	-0.000234	-0.000908
	(0.00134)	(0.00149)	(0.00360)	(0.00143)	(0.00206)	(0.00159)	(0.00116)	(0.00391)
L4.CIR	0.00142	0.00219	-0.00822*	-0.000938	0.00192	0.00147	0.000537	-0.0112**
	(0.00107)	(0.00135)	(0.00490)	(0.00210)	(0.00204)	(0.00127)	(0.00110)	(0.00490)
L.ROE	-0.00545	0.0175	0.0657***	0.00798	0.00906	-0.0118	-0.00441	-0.0786***
	(0.00640)	(0.0197)	(0.0189)	(0.0169)	(0.00947)	(0.00855)	(0.00868)	(0.0190)
L2.ROE	0.0169***	0.0118	0.0129	0.0272***	0.0127	0.0194**	-0.00148	0.0970***
	(0.00603)	(0.0126)	(0.0146)	(0.00539)	(0.00999)	(0.00814)	(0.00640)	(0.0146)
L3.ROE	0.0189***	0.00942	0.0557***	0.00766	0.0236**	0.0175*	0.0130***	0.157***
	(0.00649)	(0.00894)	(0.0127)	(0.0197)	(0.0105)	(0.00927)	(0.00468)	(0.0129)
L4.ROE	-0.0184**	-0.0304	0.0978***	-0.0236***	-0.00923	-0.0215**	-0.0241***	0.0166
	(0.00743)	(0.0244)	(0.0194)	(0.00907)	(0.0125)	(0.00920)	(0.00657)	(0.0159)
CAP	-0.00583	-2.55e-05	-0.0987***	-0.00283	-0.00296	-0.00678	0.00288	-0.0564***
	(0.00470)	(0.00457)	(0.0359)	(0.00503)	(0.0123)	(0.00433)	(0.00980)	(0.0215)
SIZE	0.00103	-4.06e-05	0.0346***	0.00115	0.000577	0.00142	-0.000998	-0.0126
	(0.00161)	(0.00184)	(0.0120)	(0.00184)	(0.00450)	(0.00159)	(0.00336)	(0.00821)
Constant	-6.683***	-6.922***	-8.862***	-6.780***	-6.801***	-6.633***	-7.078***	-14.15***
	(0.0621)	(0.228)	(0.717)	(0.112)	(0.125)	(0.0711)	(0.0727)	(0.436)
Sigma_u	0.035***	0.031***	0.034***	0.033***	0.036***	0.029***	0.033***	0.019***
Sigma_v	0.005***	0.002***	0.004***	0.005***	0.005***	0.006***	0.005***	0.003***
Lambda	7.334***	12.677***	9.321***	6.938***	7.615***	5.205***	6.938***	6.251***
Number of BANK	91	37	30	31	28	63	91	91
Observations	11,739	4,363	3,654	3,722	3,612	8,127	8,372	3,367

As shown in Table 4, the overall model fit for the full sample is 0.980, indicating the near-exhaustive explanatory power of the model, with only modest variation across subsamples. Time-varying inefficiency is substantial, accounting for 0.471 of total variance (full sample), and it dominates the contributions of core factors, control variables, and bank-level heterogeneity. This finding corroborates the results of Rahman et al. (2023). Since the inefficiency term is time-varying and may be common across banks, potential underlying drivers could include macroeconomic or financial stability factors (Islam & Nishiyama, 2016), structural shifts such as digitalization (Nguyen et al., 2023), or ESG-related dynamics (Agnese et al., 2024).

Table 4. Dominance Analysis. This table reports the result of dominance analysis with linear model. Statistic reported is Standardized Dominance Statistics of respective component and their overall fit.

	FULL	**FOR**	**GOV**	**PRIV**	**BIG-MED**	**SMALL**	**NONCOV**	**COV**
NPL	0.009	0.069	0.007	0.005	0.068	0.005	0.022	0.004
LIQ	0.003	0.012	0.005	0.002	0.035	0.005	0.007	0.003
CIR	0.012	0.023	0.014	0.015	0.014	0.022	0.023	0.033
ROE	0.287	0.421	0.475	0.422	0.386	0.375	0.430	0.451
Inefficiency	0.471	0.438	0.470	0.492	0.428	0.572	0.480	0.441
CAP	0.011	0.036	0.025	0.043	0.063	0.016	0.034	0.028
SIZE	0.004	0.003	0.003	0.022	0.006	0.005	0.005	0.040
Bank	0.182	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Other TV	0.020	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Core	0.312	0.524	0.501	0.443	0.503	0.407	0.481	0.491
Inefficiency	0.471	0.438	0.470	0.492	0.428	0.572	0.480	0.441
Control	0.015	0.039	0.029	0.065	0.069	0.021	0.038	0.068
Overall Fit	0.980	0.912	0.816	0.857	0.923	0.885	0.881	0.840

In subsample runs, the “Bank” and “Other TV” sets produced negative standardized dominance statistics, meaning that — on average across the subset regressions used by dominance analysis — including those sets reduced the chosen predictive fit. This can occur when subsampling alters predictor correlations, reduces within-subsample variability, or leaves categories sparse, which makes marginal contributions unstable (Azen & Budescu, 2003; Ray-Mukherjee et al., 2014). For brevity, we only report the subsample DA results after omitting the problematic sets; the full DA tables and diagnostics (showing the original negative values and the checks described above) are available from the authors on request.

In addition, statistical significance alone does not guarantee that the DA partition is insensitive to variable choice. To address this issue, we ran two robustness checks: (i) leave-one-variable-out (LOVO) DA to test sensitivity to individual controls, (ii) DA with addition of combined predictor (using first principal component of correlated controls-PC1). From the results, the DA partition appears robust: the aggregate shares of the core set and the SFA-based inefficiency term change only modestly under the LOVO and PC1 checks. However, the results also reveal substantial overlap between ROE and Inefficiency. Removing ROE markedly increases the Inefficiency share, and removing Inefficiency substantially raises the ROE share. This pattern reflects shared explanatory variance between these predictors, which DA reallocates depending on which variables are included.[3]

4. Conclusion

We have successfully disentangled and quantified the inefficiency component from other key contributors to NIM—namely core factors, control variables, and bank-specific heterogeneity. Time-varying inefficiency, accounting for 47.1% of the variation, dominates core components (31.2%). This suggests that banks' NIM expansion is driven more by suboptimal intermediation than by cost compensation alone. As such, improving intermediation efficiency should be a central focus of banking strategies, particularly in response to structural shifts and macroeconomic shocks.

While this study introduces an innovative approach that combines Stochastic Frontier Analysis (SFA) with Dominance Analysis (DA), we acknowledge several technical limitations. Current SFA methods do not yet account for cross-sectional dependence—an issue commonly observed in long panel datasets, including ours. There is considerable potential to develop SFA techniques that formally integrate with dominance analysis, as it is a natural extension to assess the relative contribution of inefficiency after estimating it. Future research could also extend our framework to explicitly identify the sources of inefficiency, such as macroeconomic shocks and structural changes.

Author Contributions:
Moch. Doddy Ariefianto: Conceptualization, Methodology, Formal analysis Manuscript Review, Resources
Triasesiarta Nur: Formal analysis, Literature, Manuscript Drafting, Quality Control, Resources

Open Data Statement: The data is available at Zenodo Repository with the following link: 10.5281/zenodo.17070636

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[3] These robustness checks were conducted at the request of a reviewer. Results are not tabulated here for brevity, but are available on request.

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