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Financial reporting and bank development: Evidence from Vietnam

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Abstract

An emerging research line has examined the implications of information reporting on financial intermediaries and documented adverse impacts on bank operations. We extend this literature by exploring the effects of opacity on bank development in the form of volume, quality, and costs of bank credit. Using a sample of Vietnamese commercial banks from 2007 to 2021, we find that an increase in opaque financial reporting may raise the volume of bank credit but reduce the quality and increase the costs of bank credit. These results support the view that greater bank opacity results in a large but unsafe and inefficient (i.e., high cost) banking system. Our findings are robust across alternative model specifications, different bank opacity forms via discretionary loan loss provisions and balance sheet metrics, multiple bank development measures, and different regression techniques. These findings also survive while considering the influence of the financial and health crises.

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1. Introduction

In the past decades, particularly after the 2007–2009 financial crisis, opaque financial reporting of the banking sector has become an important topic that withdraws great attention from academics and policymakers. Bank opacity denotes a lack of informativeness in the financial disclosure of banks, making outsiders (such as investors and creditors) incapable of assessing the true conditions of bank assets and values (Flannery et al., 2004). A growing strand of literature has concentrated on this controversial feature of banks and revealed conflicting evidence. Some studies suggest that bank opacity should be considered, for example to generate money more effectively (Dang et al. 2017) or mitigate rollover risk (Moreno and Takalo, 2016). Nevertheless, many studies call for policies to combat bank opacity because of its adverse impacts. For instance, more opaque banks are found to raise systemic risk (Flannery et al., 2013), suffer a drop in bank valuation (Jones et al., 2013), reduce banking stability (Acharya and Ryan, 2016), and increase the inefficiency of the financial markets (Blau et al., 2017). Regardless of opposing views on whether bank opacity is good or bad for bank operation and management, one of the clearest disadvantages of bank opacity is that insufficient informativeness to outsiders leads to weak market disciplines and creates difficulty for external fund providers to monitor banks.

This paper enlarges the existing literature by examining the impact of opaque financial reporting on bank development. Our core identification strategy is inspired by the fact that a banking system will be developed if banks could expand the quantity of their loan supply at low cost and with low risk (Ashraf, 2018). So, we approach bank development in the form of the volume, quality, and costs of bank credit. We measure the volume of bank credit by the annual growth rate of gross loans (and the ratio of gross loans to total assets as an alternative measure). We employ loan loss reserves as a share of gross loans to capture bank risk or the inverse measure of bank credit quality (and non-performing loans divided by gross loans for the robustness check). The credit costs are estimated using net interest margins (and the ratio of interest income to total earning assets alternatively used in the robustness test). For the proxy of opaque financial reporting, we follow the existing literature in using discretionary loan loss provisions (Beatty and Liao, 2014; Desalegn and Zhu, 2021; Jiang et al., 2016; Tran et al., 2019; Tran and Ashraf, 2018). Given that loan loss provisions reveal present estimation for future losses, prior authors claim that the ambiguity while estimating such provisions gives bank managers great flexibility in manipulating banks' earnings and capital levels. So, discretionary loan loss provisions are widely employed to effectively indicate financial disclosure informativeness.

To conduct the empirical analysis, we collect financial data from a panel of Vietnamese commercial banks over the period from 2007 to 2021. We empirically perform our regression works using fixed effects with corrected Driscoll-Kraay standard errors and the two-step system generalized method of moments (GMM) estimator. Some additional tests are further carried out to ensure the robustness of our findings. First, we use alternative measures of bank development, which are associated with the volume, quality, and costs of bank credit as outlined above. Second, we adopt an adjusted model of loan loss provisions and approach banking items on and off the balance sheets to alternatively measure bank opacity. Third, we rely on the least squares dummy variable corrected (LSDVC) estimator to alleviate concern for regressions in a small and heavily unbalanced panel dataset. Fourth, we utilize a subsample analysis to wipe out the influences caused by the financial crisis of 2007–2009 and the COVID-19 pandemic of 2020–2021 that potentially alter our estimates.

Vietnam introduces an attractive case study for performing the analysis. Since the capital market in Vietnam has been somewhat underdeveloped, the banking sector has repeatedly played a vital role in fueling economic growth, primarily via bank credit (Dang and Huynh

2022). This circumstance highlights the importance of bank credit and bank development, making bank credit a critical aspect that has to be appropriately supervised for bank development and economic growth. However, bank credit in Vietnam has gone through periods of unstable development, featured by uncontrolled high credit growth peaking in 2009 and booming bad debts in 2012 (Dang 2020).

Vietnamese banks are encouraged to be listed on the stock exchange to increase the levels of transparency and disclosures in the banking sector (Le, 2020). However, the transparency in information disclosure of the Vietnamese banking sector created a big concern when it was considered quite limited, especially when compared to some counterparts in emerging markets (Batten and Vo, 2019). As of 2021, the Vietnamese banking industry is in a critical preparation phase for applying the International Financial Reporting Standards 9 (IFRS 9) according to a proposed roadmap. Also, it could be seen that due to the effects of international integration and suggestions from the third pillar of the Basel III framework on market discipline, the financial reporting practice of banks in Vietnam has experienced some changes. Contributing to these changes is the role of external audit, when external audit quality may raise the efficiency of financial reporting. The SBV and banks themselves also identified the important role played by external audit quality in relation to bank stability (Nguyen and Dang, 2019). As a market supervisor who highlights supervisory discipline, SBV has legalized banking management standards according to Basel II and required commercial banks to enforce them. Thus far, under the requirements of the SBV, the entire banking system in Vietnam has not yet definitely finished the requirements from Basel II.

This paper brings some contributions to the literature. Most importantly, it is the first to explore the impact of opaque financial reporting on bank development as captured by the volume, quality, and costs of bank credit. Looking at all these aspects allows us to provide a fresh and relatively comprehensive assessment of banking development. Previous studies have examined individual dimensions of bank credit (i.e., loan growth and credit risk) but failed to consider all of them simultaneously. Concretely, Zheng (2020) indicates a negative impact of bank opacity on US loan growth, while Fosu et al. (2017) reveal that opacity increases bank risk-taking in the US market, which is also witnessed in the work of Cao and Juelsrud (2022) for the Norwegian banking sector. To the best of our knowledge, no study has been done to shed light on the effect of bank opacity on credit costs. Additionally, it is worth noticing that this paper complements the related studies by focusing entirely on an emerging market. Unlike developed economies that have been taken care of in previous studies (Cao and Juelsrud, 2022; Fosu et al., 2017; Zheng, 2020), emerging markets like Vietnam display differences in terms of market discipline, information disclosure, and bank lending behaviors. Therefore, further studies are needed for emerging markets in the context results from previous studies are of limited application to these markets. The analysis of this study provides important implications for transparency issues in financial reporting and disciplines in the market, contributing to the ongoing architecture of the Basel III framework in Vietnam as well as other emerging economies.

We structure the remainder of this paper as follows. Section 2 reviews the related literature on the effect mechanisms of financial reporting on different dimensions of bank credit. Section 3 exhibits our empirical approach to gain estimation results, which are then reported in section 4. Also, section 4 provides some additional tests to strengthen the reliability of our findings. Finally, section 5 concludes the entire research with policy implications.

2. The effect mechanisms of opaque financial reporting

Financial reporting is closely associated with corporate governance and market discipline – the process in which banks may employ available information to monitor their excessive risk-taking. Accordingly, increased opacity could weaken corporate governance and market discipline, thus mitigating incentives and efforts banks invest in monitoring and screening (Boot and Schmeits, 2000; Bushman and Smith, 2001). This mechanism ultimately results in the bank's higher risk of default.

When committing to weaker market disciplines, opaque banks signal to the market that they are unsafe. In turn, these banks receive a penalty of higher financing costs from their creditors and investors (Berlin and Loeys, 1988). On the one hand, this increase in financing costs boosts the cost of bank credit correspondingly, and on the other hand, forces banks to adopt high risk-taking strategies (Cordella and Yeyati, 1998; Nier, 2005). Besides, when facing opaque banks that tend to manipulate their financial information, fund suppliers (as outsiders) are uncertain about these banks' financial status. So, these suppliers subsequently respond by withdrawing the funds or canceling the additional funding supply (Shin, 2009). Under the above-elaborated mechanisms (i.e., associated with a rise in funding costs and a drop in the funding supply), banks have to restrain their credit supply.

However, there are also strong arguments that contrast the mechanisms discussed above, thereby suggesting opposing views on the impacts of opacity on the development of banks. One of the critical arguments belongs to the motive of decreased information disclosure – the regulatory capital requirement (Barth et al., 2017). Accordingly, financial information management can alleviate pressure on the bank's capital buffers, thereby helping to maintain lending activities less dependent on the capital adequacy requirement (Acharya and Ryan, 2016). In another vein, contrary to the benefit implications of financial transparency, some theories point to the costs associated with transparency. For example, transparency likely leads to inefficient bank runs ruled by coordination failures (Morris and Shin, 2002) and potentially hurts bank managers' incentives, which increases the likelihood of banks making poor investment decisions (Goldstein and Sapra, 2014).

Taken together, due to the lack of consensus on the underlying mechanisms, we realize that how opaque financial reporting affects bank development, as captured from the perspective of the volume, quality, and costs of bank credit, deserves empirical attention.

3. Data and methodology

3.1 Data

We collect data on annual financial reports of commercial banks in Vietnam from 2007 to 2021. We obtain our sample after using the following principles: (i) excluding banks that are acquired or under special control by the state due to the differences in regulatory constraints and business scopes, and (ii) excluding banks without data available for at least four consecutive years. The macroeconomic data is sourced from the Global Financial Development database. Overall, our sample forms an unbalanced panel, covering 31 commercial banks with a maximum of 449 bank-year observations and illustrating roughly 90% of the Vietnamese banking sector (based on total assets). We winsorize bank-level data at the 1st and 99th percentiles.

3.2 Bank opacity measure

In this subsection, we describe the procedure we construct our main opacity measure from the perspective of bank earnings management. Consistent with the former literature, we establish a model of loan loss provisions regressed by a range of bank-level and macro-level variables to estimate discretionary loan loss provisions. In the context that no most ideal model has been identified among multiple different variants observed in the literature, we specify our regression model based on the version with parsimonious input data of some recent authors (Jiang et al., 2016; Tran et al., 2019; Tran and Ashraf, 2018) as follows:[1]

$$Llp_{i,t} = \alpha_0 + \alpha_1 \times \Delta Npl_{i,t+1} + \alpha_2 \times \Delta Npl_{i,t} + \alpha_3 \times \Delta Npl_{i,t-1} + \alpha_4 \times Size_{i,t-1} + \alpha_5 \times \Delta Loan_{i,t} + \alpha_6 \times \Delta GDP_t + \alpha_7 \times \Delta Unemployment_t + \varepsilon_{i,t} \quad (1)$$

where i and t capture banks and years, respectively. The dependent variable denotes loan loss provisions scaled by lagged total loans. ΔNpl is the change in non-performing loans as a share of lagged total loans; subject to data availability restraints, we take into account the changes in non-performing loans in the last year ($\Delta Npl_{i,t-1}$), the current year ($\Delta Npl_{i,t}$), and the next year ($\Delta Npl_{i,t+1}$). *Size* captures the natural logarithm of total assets, and $\Delta Loan$ is the change in total loans divided by lagged total assets. For macro-level variables, ΔGDP and $\Delta Unemployment$ highlight the changes in the GDP growth rates and the unemployment rates, respectively.[2]

Our regression model shows that its residuals $\varepsilon_{i,t}$ gain excellent predictive power in estimating loan loss provisions for bank observations, thus a larger value of the residuals (in absolute values) indicates a higher level of earnings management or bank opacity. We regress the model and calculate and report the distribution of the opacity measure in Table 1. We realize that the average of this measure for Vietnam is 0.012 with a standard deviation of 0.007. These figures are comparable to those displayed in the previous papers that utilize the absolute residuals from the model regression of loan loss provisions as an opacity proxy (Desalegn and Zhu, 2021; Tran et al., 2019; Tran and Ashraf, 2018).[3]

3.3 Model specification and econometric technique

The paper identifies the impact of financial reporting on bank development in the forms of different bank credit dimensions by employing the model specification as follows:

$$Y_{i,t} = \alpha_0 + \alpha_1 \times Opacity_{i,t-1} + \alpha_2 \times X_{i,t-1} + \alpha_3 \times Z_{t-1} + v_i + \varepsilon_{i,t} \quad (2)$$

The dependent variable $Y_{i,t}$ indicates different bank development aspects including the quantity, quality, and costs of bank credit, measured by the loan growth rate, the loan loss reserves (as a share of gross loans), and the net interest margins, respectively. The independent variable of main interest $Opacity_{i,t-1}$ is proxied by discretionary loan loss provisions as described earlier. Motivated by the well-established evidence on the determinants of bank credit volume, quality and costs (Chaibi and Ftiti, 2015; Maudos and Solís, 2009; Roulet, 2018; Çolak and Öztekin, 2021), we include multiple control variables in the model: a vector of bank-level controls ($X_{i,t-1}$) covers bank capital, liquidity positions, bank size, and noninterest income; a series of macro-level controls (Z_{t-1}) consists of economic growth, refinancing rates,

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[1] We do not consider bank fixed effects in our equation (1) since we are following the provision model of many prior authors. For specific references, please see Beatty and Liao (p.366, 2014), Desalegn and Zhu (p.1005, 2021), Tran et al. (p.163, 2019), and Tran and Ashraf (p.4, 2018). There are also some authors who explore bank opacity but do not employ bank fixed effects in the first stage of their models. For example, Jiang et al. (2016) do not use bank fixed effects in the first stage of their provision model but utilize bank fixed effects in the second stage when examining the relationship between bank competition and opacity. To handle a concern that failure to take into account bank fixed effects in the provision model could significantly alter our results, we re-estimate the first stage of our provision model by including bank fixed effects and then re-estimate the models focusing on the impacts of bank opacity. Our untabulated estimates suggest that our main finding still holds; thus, whether or not controlling bank time fixed effects does not change our results. We thank an anonymous reviewer for the comment to pay attention to bank fixed effects in our provision model.

[2] As we already have macro-level factors to control for macro-economic conditions, we do not include time fixed effects to avoid overlap. Moreover, the inclusion of time fixed effects is costly compared to our parsimonious model specification and data as it may reduce many freedom degrees.

[3] The results for the coefficients on regressors of equation (1) are not tabulated in this manuscript to save space but are available upon request.

the financial crisis, and the COVID-19 pandemic. We describe all controls in Table 1. v_i denotes bank fixed effects and $\varepsilon_{i,t}$ reflects the error term. We lag all variables on the right-hand side of the equation by one year to (i) mitigate the possible reverse causality and (ii) emphasize lagged reactions in bank development to balance sheet and macroeconomic shocks.

Table 1. Summary statistics and definitions of regression variables

	Obs	Mean	SD	Min	Max	Definitions
LGR	441	27.569	26.548	–2.358	101.758	Loan growth rate (%)
LLR	449	1.263	0.500	0.502	2.449	Loan loss reserves, as a share of gross loans (%)
NIM	449	2.824	1.061	0.980	5.185	Net interest margins (%)
Opacity	388	0.012	0.007	0.002	0.026	Discretionary loan loss provisions
Capital	449	9.745	4.312	4.902	20.470	Equity to total assets (%)
Liquidity	449	33.363	10.750	17.625	55.780	Liquid assets to total assets (%)
Size	449	32.113	1.256	29.975	34.405	Natural logarithm of total assets
NIIshare	449	21.608	13.663	–2.282	52.823	Non-interest income to operating income (%)
Refinancing rates	449	7.521	2.733	4.000	15.000	Refinancing rates set up by the central bank of Vietnam (%)
GDP growth	449	5.807	1.313	2.580	7.130	Real GDP, annual growth rate (%)
Crisis	449	0.185	0.389	0.000	1.000	=1 during financial crisis years 2007–2009
COVID-19	449	0.127	0.333	0.000	1.000	=1 during COVID-19 pandemic years 2020–2021

The Hausman test (not reported) identifies that the fixed-effects estimator is preferable to the random-effects estimator. So, we rely on corrected Driscoll-Kraay standard errors to obtain fixed-effects regression results that are heteroscedasticity consistent and robust to general forms of cross-sectional and temporal dependence (Hoechle, 2007). Apart from fixed-effects regressions, we extend our model by the lagged dependent variable as a regressor and then utilize the GMM estimator to deal with the endogeneity bias and consider the dynamic nature of bank development (Roodman, 2009). Some diagnostics are required to validate the GMM results, i.e., the Hansen test for the over-identification in estimations and the AR(1)/AR(2) tests for the first- and second-order autocorrelation.

4. Results

4.1 Main estimation results

We present the regression results investigating the effects of opaque financial reporting on the volume of bank credit in Table 2, the quality of bank credit in Table 3, and the cost of bank credit in Table 4. Across all tables, we first exhibit a univariate regression of different dependent variables on bank opacity; we subsequently insert bank-level controls and finally add macro-level controls. We regress our models with fixed effects and two-step system GMM estimators. All estimates obtained by the dynamic GMM estimator are validated by the significant lagged dependent variable and the outcomes of necessary tests.

We look into the results in Table 2, where we employ the loan growth rate as the dependent variable. The coefficient of bank opacity is positive and statistically significant in all columns, supporting the positive link between earnings management and bank loan growth. This finding indicates that bank earnings management promotes bank development through enhancing the expanded quantity of bank lending. The economic significance of this finding is also certified via the magnitude of the estimated coefficients. For instance, a one standard deviation rise in the opacity proxy (0.007) is associated with a 3.889 – 10.459 percentage point increase in the loan growth rate (555.567*0.007 – 1,494.073*0.007), whose sample mean is 27.569%.

Table 2. Opacity and the volume of bank credit

	Dependent variable: Loan growth rate					
	Fixed effect regressions			System GMM regressions		
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged dependent variable				0.341***	0.174***	0.279***
				(0.016)	(0.017)	(0.019)
Opacity	621.916**	725.579**	687.894**	555.567***	1,494.073***	1,066.608***
	(236.029)	(308.316)	(292.051)	(127.237)	(176.588)	(279.218)
Size		–9.803**	–14.550***		–7.179***	–5.155***
		(3.310)	(3.166)		(1.049)	(0.978)
Capital		0.587	0.567		–0.194	0.170
		(0.502)	(0.434)		(0.288)	(0.233)
Liquidity		0.514**	0.755***		0.496***	0.460***
		(0.177)	(0.142)		(0.042)	(0.088)
NIIshare		0.136	0.057		0.312***	0.228***
		(0.202)	(0.162)		(0.034)	(0.042)
GDP			4.220*			1.477
			(1.964)			(1.180)
Refinancing rates			–2.690***			–1.669***
			(0.527)			(0.214)
Crisis			7.432			34.450***
			(4.587)			(4.243)
COVID-19			11.803			–0.322
			(8.712)			(4.946)
Observations	387	387	387	356	356	356
Banks	31	31	31	31	31	31
R-squared	0.026	0.267	0.356			
Instruments				21	25	29
AR(1) test (p-value)				0.001	0.001	0.000
AR(2) test (p-value)				0.845	0.829	0.549
Hansen test (p-value)				0.286	0.297	0.356

Notes: The table reports the results for the effect of earnings opacity on bank development as captured by the volume of bank credit. Columns 1–3 are estimated employing fixed-effects regression models with Driscoll-Kraay standard errors, whereas columns 4–6 are estimated by the two-step system GMM estimator. Standard errors are presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Next, we turn to discuss the results based on the credit risk measure presented in Table 3. We observe that the coefficient of the opacity variable is significantly positive in all regressions of loan loss reserves that highlight the reverse quality of bank credit. Based on the face values of the coefficients, we can infer that an increase of one standard deviation in bank opacity may cause a 0.067 – 0.103 percentage point rise in the loan loss reserves ratio (9.642*0.007 – 14.647*0.007), given that the average value of this credit risk measure is 1.263%. Both statistical and economic significance of the regression results justifies that banks engaging more in earnings management are more likely to suffer a decline in the quality of bank credit or an increase in bank risk.

We now move on to the relationship between bank opacity and net interest margins, as reported in Table 4. We find that discretionary loan loss provisions are positively associated with NIM. This link is statistically significant across all specifications, and the magnitude of the impact is also economically significant. For illustration, we can suggest that an increase of one standard deviation in bank opacity may lead to an increase of 0.093 – 0.195 percentage points in net interest margins (13.351*0.007 – 27.890*0.007), given that the sample mean of NIM is 2.824%. Hence, our results reveal that a higher level of earnings manipulations triggers the cost of bank lending.

Table 3. Opacity and the quality of bank credit

	Dependent variable: Loan loss reserves					
	Fixed effect regressions			System GMM regressions		
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged dependent variable				0.617***	0.704***	0.493***
				(0.021)	(0.024)	(0.030)
Opacity	14.062***	14.647***	13.586***	9.642***	10.847***	12.829**
	(2.530)	(1.963)	(1.786)	(0.847)	(1.210)	(5.020)
Size		–0.008	0.085		–0.052***	0.009
		(0.060)	(0.055)		(0.007)	(0.015)
Capital		–0.008*	–0.015***		–0.018***	–0.020***
		(0.005)	(0.002)		(0.003)	(0.002)
Liquidity		–0.003**	–0.008***		0.001	–0.002**
		(0.001)	(0.001)		(0.001)	(0.001)
NIIshare		–0.001	0.003***		0.002***	0.003***
		(0.002)	(0.001)		(0.001)	(0.001)
GDP			–0.270***			–0.121***
			(0.024)			(0.022)
Refinancing rates			0.033***			0.036***
			(0.007)			(0.003)
Crisis			–0.333***			–0.130***
			(0.058)			(0.027)
COVID-19			–1.015***			–0.355***
			(0.106)			(0.099)
Observations	387	387	387	387	387	387
Banks	31	31	31	31	31	31
R-squared	0.049	0.066	0.272			
Instruments				21	25	29
AR(1) test (p-value)				0.000	0.000	0.000
AR(2) test (p-value)				0.421	0.409	0.320
Hansen test (p-value)				0.285	0.311	0.506

Notes: The table reports the results for the effect of earnings opacity on bank development as captured by the quality of bank credit. Columns 1–3 are estimated employing fixed-effects regression models with Driscoll-Kraay standard errors, whereas columns 4–6 are estimated by the two-step system GMM estimator. Standard errors are presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Overall, our findings show that greater earnings management effectively raises the volume of bank credit but is harmful to the costs and quality of bank lending. Estimation results are similar with specifications controlling for different sets of variables using alternative econometric techniques, including corrected Driscoll-Kraay fixed effects versus GMM regressions. For the positive impact of bank opacity on loan growth, our finding is at odds with Zheng (2020) who documents that opacity exerts a negative influence on loan growth in the US market. A possible reason for this difference is as follows. Different from developed markets like the US, the banking sector in Vietnam institutes the dominant funding source for real economic sectors (Dang and Huynh 2022). Capital buffers of Vietnamese banks are much thinner than those of their counterparts in developed markets (Haq et al. 2018; Dang and Nguyen 2021), so limited financial information disclosure is more likely to reduce pressure on capital adequacy requirements and help banks maintain their lending potential in Vietnam (Acharya and Ryan, 2016). With respect to the harmful effect of earnings manipulations on bank credit quality, our finding complements those by Fosu et al. (2017) and Cao and Juelsrud (2022) that opacity increases bank risk-taking. Prior authors use analysts' forecasts and balance sheet items to measure different categories of bank opacity. Our analysis in this regard may contribute to the work of Foos et al. (2010) that an increase in bank loan growth is offset by an increase in the risk of bank asset portfolios. Importantly, our finding that credit costs increase at more opaque banks is entirely novel in the empirical literature. It aligns with the notion that opaque banks may confront high funding costs due to the market's judgment that treats them as of unsafe banks (Cordella and Yeyati, 1998; Nier, 2005). An increase in funding costs (i.e., input costs) may lead to an increase in output costs (i.e., the cost of bank credit) to a greater extent, since the elasticity of lending rates is larger than that of deposit rates (Hancock, 1985). In addition, rising funding costs also push banks to take over more risk, which is consistent with previous arguments (Cao and Juelsrud, 2022; Fosu et al., 2017).

Table 4. Opacity and the cost of bank credit

	Dependent variable: Net interest margins					
	Fixed effect regressions			System GMM regressions		
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged dependent variable				0.569***	0.650***	0.622***
				(0.025)	(0.034)	(0.045)
Opacity	27.890***	17.190**	22.897***	16.202***	13.351***	20.776***
	(3.299)	(5.804)	(5.347)	(1.405)	(2.070)	(7.195)
Size		0.193*	0.626***		–0.013	0.053
		(0.105)	(0.174)		(0.025)	(0.052)
Capital		0.087***	0.099***		–0.018***	–0.003
		(0.026)	(0.025)		(0.007)	(0.015)
Liquidity		0.009	–0.004		0.012***	0.008***
		(0.005)	(0.004)		(0.002)	(0.002)
NIIshare		–0.014***	–0.013***		0.006***	0.003
		(0.004)	(0.004)		(0.001)	(0.002)
GDP			–0.045			0.264***
			(0.060)			(0.045)
Refinancing rates			0.157***			0.108***
			(0.022)			(0.010)
Crisis			0.325*			0.116
			(0.182)			(0.076)
COVID-19			0.095			1.285***
			(0.252)			(0.194)
Observations	388	387	387	387	387	387
Banks	31	31	31	31	31	31
R-squared	0.043	0.176	0.337			
Instruments				21	25	29
AR(1) test (p-value)				0.000	0.000	0.000
AR(2) test (p-value)				0.881	0.887	0.354
Hansen test (p-value)				0.242	0.266	0.367

Notes: The table reports the results for the effect of earnings opacity on bank development as captured by the costs of bank credit. Columns 1–3 are estimated employing fixed-effects regression models with Driscoll-Kraay standard errors, whereas columns 4–6 are estimated by the two-step system GMM estimator. Standard errors are presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

4.2 Robustness checks

Thus far, our examination yields three key results: (i) bank credit supply increases in response to earnings management, (ii) more opaque banks suffer more credit risk, and (iii) bank opacity leads to higher costs of bank credit. In this subsection, we desire to offer additional tests to strengthen these findings.

First, we check the sensitivity of our estimates to alternative measures of bank development from the perspective of the bank credit segment. Our alternative measure for the volume of bank credit is computed by gross loans as a share of total assets (*Loan share*). Next, our alternative measure for the quality of bank lending is the ratio of non-performing loans to gross loans (*NPL*). Finally, we use the ratio of interest income to total earning assets to alternatively capture bank credit costs (*InterestEA*). It should be noted that the use of this alternative credit cost variable is suitable to neutralize the concern that our NIM variable allows for both interests paid for deposits and interests earned from loans. We repeat the estimations and present the results in Table 5. We observe that our findings remain unchanged when using all alternative variables capturing bank development.

Second, we apply alternative proxies of bank opacity. We first adjust our model of loan loss provisions by adopting the preferred one of Beatty and Liao (2014). To this end, we expand the list of bank-level estimators by loan loss allowances and net charge offs (both are scaled by lagged total loans).[4] Following some prior authors (Jiang et al., 2016; Tran et al., 2019), after having the absolute values of the error term, we take its natural logarithm form to gain an alternative bank opacity proxy that can mitigate the effects of outliers. We also take a further step to look into other forms of bank opacity, which emerges from the shortage of financial information on and off bank balance sheets. Inspired by Cao and Juelsrud (2022), we utilize two opacity proxies, namely, the ratio of total assets to available-for-sale securities (since these available-for-sale securities are priced by market participants, thus they indicate more transparency) and the ratio of off-balance sheet items to total assets (since there is limited information available for outsiders due to the payoff nature of off-balance sheet activities).[5] We re-estimate our models using the alternative proxies of bank opacity as discussed above and report the results in Tables 6–8. Overall, we can witness that our key findings remain unaltered.

Third, we apply an alternative econometric technique to perform regressions. Given that our panel dataset contains a limited number of cross-section units and exhibits a highly unbalanced nature, we choose the LSDVC estimator to tackle such weaknesses in our data sample (Bruno, 2005). We conduct the LSDVC estimations using bootstrapped standard errors with 100 iterations and report the Anderson-Hsiao LSDVC procedure in Table 9 (for other versions Arellano-Bond and Blundell-Bond of the LSDVC estimator, the results are similar). The coefficient on the opacity variable indicates that an increase in the level of bank earnings management significantly increases bank loan growth but also raises the costs and risks of bank credit. Hence, our findings are robust to changing the econometric technique.

Fourth, we use subsamples to perform our checks. Our approach is motivated by the fact that our dataset includes two global crises that can cause considerable structural breaks in banks' behaviors. These two crises are the financial crisis of 2007–2009 and the health crisis of 2020–2021 (caused by the COVID-19 pandemic). For example, the rise in the levels of bank opacity (Flannery et al., 2013) and the decline in bank credit supply (Ivashina and Scharfstein, 2010; Çolak and Öztekin, 2021), which are simultaneous trends during the crisis times, may plague our estimates. To deal with this issue, we run analyses excluding the financial crisis years (2007–2009), eliminating the health crisis years (2020–2021), and dropping the periods of both crises in the sample. We report all results for different subsamples in Table 10. Once again, we find that our key results are maintained.

[4] For more detail in this setting with the inclusion of both loan loss allowance and net charge off, please refer to the specific demonstration of Beatty and Liao (2014).

[5] Please refer to the paper of Cao and Juelsrud (2022) for the use of these two forms of opacity.

Table 5. Robustness checks with alternative measures for the volume, quality and cost of bank credit

	Dependent variable: Loan share		Dependent variable: NPL		Dependent variable: InterestEA	
	Fixed effect	GMM	Fixed effect	GMM	Fixed effect	GMM
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged dependent variable		0.601***		0.393***		0.473***
		(0.065)		(0.043)		(0.027)
Opacity	74.006**	184.515***	18.996*	27.572**	53.908**	125.846***
	(29.940)	(52.653)	(9.758)	(13.853)	(23.058)	(17.210)
Size	1.007	1.922***	0.026	–0.380***	0.509	–0.157
	(1.205)	(0.449)	(0.059)	(0.114)	(0.376)	(0.103)
Capital	0.005	–0.021	–0.010	–0.062***	–0.014	–0.044
	(0.128)	(0.124)	(0.019)	(0.021)	(0.016)	(0.036)
Liquidity	–0.843***	–0.028	–0.027***	–0.015***	0.139***	0.074***
	(0.081)	(0.058)	(0.005)	(0.003)	(0.019)	(0.009)
NIIshare	–0.062**	–0.076***	0.003	0.006***	0.010	–0.003
	(0.024)	(0.014)	(0.005)	(0.002)	(0.008)	(0.004)
GDP	2.090*	1.479***	–0.752***	0.054	–2.233***	0.834***
	(0.983)	(0.450)	(0.094)	(0.046)	(0.626)	(0.121)
Refinancing rates	–0.522***	–0.455***	0.059***	0.117***	1.245***	1.103***
	(0.133)	(0.075)	(0.010)	(0.013)	(0.108)	(0.044)
Crisis	3.658**	5.195***	–0.832***	–0.477***	–4.090***	–4.260***
	(1.261)	(0.809)	(0.113)	(0.074)	(0.858)	(0.251)
COVID-19	0.794	4.203**	–2.920***	0.013	–6.618**	5.462***
	(1.350)	(1.793)	(0.339)	(0.084)	(2.651)	(0.479)
Observations	387	356	351	331	357	356
Banks	31	31	31	31	31	31
R-squared	0.751		0.235		0.743	
Instruments		29		29		29
AR(1) test (p-value)		0.000		0.000		0.000
AR(2) test (p-value)		0.859		0.146		0.841
Hansen test (p-value)		0.499		0.447		0.294

Notes: The table reports the results for the effect of earnings opacity on bank development as captured by the volume, quality, and costs of bank credit. The dependent variables are displayed at the head of each column. Columns 1, 3, and 5 are estimated employing fixed-effects regression models with Driscoll-Kraay standard errors, whereas columns 2, 4, and 6 are estimated by the two-step system GMM estimator. Standard errors are presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 6. Robustness checks with an alternative calculation of discretionary loan loss provisions

	Dependent variable: LGR		Dependent variable: LLR		Dependent variable: NIM	
	Fixed effect	GMM	Fixed effect	GMM	Fixed effect	GMM
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged dependent variable		0.242***		0.526***		0.634***
		(0.016)		(0.033)		(0.035)
ln(Opacity)	8.861**	11.285***	0.104***	0.107***	0.190***	0.189***
	(3.271)	(1.990)	(0.021)	(0.013)	(0.038)	(0.031)
Size	–14.465***	–7.500***	0.094*	0.006	0.639***	0.036
	(3.044)	(1.966)	(0.049)	(0.012)	(0.164)	(0.052)
Capital	0.478	–0.119	–0.013***	–0.020***	0.101***	–0.003
	(0.384)	(0.345)	(0.003)	(0.002)	(0.023)	(0.014)
Liquidity	0.727***	0.448***	–0.008***	–0.001*	–0.004	0.007***
	(0.136)	(0.094)	(0.001)	(0.001)	(0.004)	(0.003)
NIIshare	0.073	0.208***	0.003***	0.003***	–0.013***	0.004*
	(0.150)	(0.042)	(0.001)	(0.001)	(0.004)	(0.002)
GDP	4.238**	1.073	–0.273***	–0.118***	–0.050	0.272***
	(1.833)	(1.314)	(0.024)	(0.020)	(0.062)	(0.037)
Refinancing rates	–2.596***	–2.029***	0.032***	0.035***	0.157***	0.113***
	(0.442)	(0.344)	(0.007)	(0.003)	(0.022)	(0.010)
Crisis	8.654*	32.530***	–0.332***	–0.128***	0.332*	0.081
	(4.205)	(4.206)	(0.053)	(0.021)	(0.180)	(0.078)
COVID-19	11.910	–2.605	–1.030***	–0.343***	0.073	1.338***
	(8.054)	(5.535)	(0.109)	(0.095)	(0.259)	(0.159)
Observations	387	356	387	387	387	387
Banks	31	31	31	31	31	31
R-squared	0.382		0.258		0.331	
Instruments		29		29		29
AR(1) test (p-value)		0.000		0.000		0.000
AR(2) test (p-value)		0.469		0.375		0.304
Hansen test (p-value)		0.439		0.391		0.432

Notes: The table reports the results for the effect of earnings opacity on bank development as captured by the volume, quality, and costs of bank credit. The dependent variables are displayed at the head of each column. Columns 1, 3, and 5 are estimated employing fixed-effects regression models with Driscoll-Kraay standard errors, whereas columns 2, 4, and 6 are estimated by the two-step system GMM estimator. Standard errors are presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 7. Robustness checks with an alternative proxy for bank opacity: Available-for-sale securities

	Dependent variable: LGR		Dependent variable: LLR		Dependent variable: NIM	
	Fixed effect	GMM	Fixed effect	GMM	Fixed effect	GMM
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged dependent variable		0.276***		0.562***		0.609***
		(0.022)		(0.036)		(0.054)
SecurityAFS (inverse)	0.361*	0.380***	0.012**	0.003*	0.011**	0.006*
	(0.172)	(0.129)	(0.005)	(0.002)	(0.005)	(0.004)
Size	–15.053***	–2.003***	0.100	0.049***	0.727***	0.112**
	(3.660)	(0.543)	(0.062)	(0.013)	(0.161)	(0.049)
Capital	0.688	0.559***	–0.004	–0.010***	0.116***	0.008
	(0.411)	(0.176)	(0.003)	(0.003)	(0.019)	(0.015)
Liquidity	0.684***	0.321***	–0.009***	–0.001	–0.006	0.008***
	(0.200)	(0.115)	(0.001)	(0.002)	(0.004)	(0.003)
NIIshare	0.184	0.222***	0.002**	0.003***	–0.015***	0.004
	(0.125)	(0.033)	(0.001)	(0.001)	(0.004)	(0.003)
GDP	4.197***	–0.154	–0.278***	–0.139***	–0.039	0.233***
	(1.065)	(1.114)	(0.025)	(0.018)	(0.065)	(0.033)
Refinancing rates	–2.086***	–1.323***	0.036***	0.034***	0.157***	0.113***
	(0.214)	(0.392)	(0.006)	(0.003)	(0.023)	(0.010)
Crisis	20.827***	39.173***	–0.313***	0.000	0.418**	0.092
	(1.817)	(4.321)	(0.048)	(0.000)	(0.186)	(0.063)
COVID-19	14.324**	–7.077	–0.906***	–0.336***	0.162	1.301***
	(4.900)	(5.294)	(0.136)	(0.085)	(0.307)	(0.150)
Observations	379	379	409	409	409	409
Banks	31	31	31	31	31	31
R-squared	0.442		0.245		0.335	
Instruments		29		29		29
AR(1) test (p-value)		0.000		0.000		0.000
AR(2) test (p-value)		0.828		0.144		0.502
Hansen test (p-value)		0.390		0.181		0.408

Notes: The table reports the results for the effect of earnings opacity on bank development as captured by the volume, quality, and costs of bank credit. The dependent variables are displayed at the head of each column. *SecurityAFS (inverse)* is the opacity proxy, computed by the ratio of total assets to available-for-sale securities. Columns 1, 3, and 5 are estimated employing fixed-effects regression models with Driscoll-Kraay standard errors, whereas columns 2, 4, and 6 are estimated by the two-step system GMM estimator. Standard errors are presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 8. Robustness checks with an alternative proxy for bank opacity: Off-balance sheet items

	Dependent variable: LGR		Dependent variable: LLR		Dependent variable: NIM	
	Fixed effect	GMM	Fixed effect	GMM	Fixed effect	GMM
	(1)	(2)	(3)	(4)	(5)	(6)
Lagged dependent variable		0.195**		0.449***		0.584***
		(0.094)		(0.050)		(0.084)
OffBLS	0.124**	0.007	0.005	0.004***	0.017***	0.008***
	(0.055)	(0.235)	(0.004)	(0.001)	(0.004)	(0.002)
Size	–12.988**	–6.895	0.028	–0.007	0.472***	0.102
	(4.439)	(10.838)	(0.055)	(0.033)	(0.112)	(0.065)
Capital	1.398*	–0.705	0.004	–0.002	0.086***	0.013
	(0.649)	(2.119)	(0.008)	(0.007)	(0.022)	(0.017)
Liquidity	0.956***	0.480*	–0.006*	–0.006**	0.002	0.011***
	(0.301)	(0.262)	(0.003)	(0.002)	(0.003)	(0.004)
NIIshare	0.206	0.096	0.001	0.002*	–0.015**	0.004
	(0.198)	(0.126)	(0.003)	(0.001)	(0.005)	(0.005)
GDP	3.359*	–2.206	–0.251***	–0.213***	–0.136	0.225***
	(1.807)	(3.772)	(0.028)	(0.043)	(0.102)	(0.047)
Refinancing rates	–1.827***	–1.661***	0.028***	0.021***	0.167***	0.136***
	(0.254)	(0.589)	(0.004)	(0.004)	(0.013)	(0.009)
Crisis	7.650***	28.178***	–0.309***	–0.255***	0.087	–0.003
	(2.035)	(10.798)	(0.076)	(0.087)	(0.172)	(0.062)
COVID-19	9.547	0.000	–0.964***	–0.812***	0.000	0.000
	(7.279)	(0.000)	(0.135)	(0.183)	(0.000)	(0.000)
Observations	379	379	409	409	409	409
Banks	31	31	31	31	31	31
R-squared	0.461		0.159		0.332	
Instruments		29		29		29
AR(1) test (p-value)		0.019		0.003		0.004
AR(2) test (p-value)		0.882		0.613		0.758
Hansen test (p-value)		0.339		0.390		0.312

Notes: The table reports the results for the effect of earnings opacity on bank development as captured by the volume, quality, and costs of bank credit. The dependent variables are displayed at the head of each column. *OffBLS* is the opacity proxy, computed by the ratio of off-balance sheet items to total assets. Columns 1, 3, and 5 are estimated employing fixed-effects regression models with Driscoll-Kraay standard errors, whereas columns 2, 4, and 6 are estimated by the two-step system GMM estimator. Standard errors are presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 9. Robustness checks with the LSDVC estimator

	(1) LGR	(2) LLR	(3) NIM
Lagged LGR	0.276***		
	(0.019)		
Lagged LLR		0.545***	
		(0.026)	
Lagged NIM			0.648***
			(0.040)
Opacity	931.026***	7.212***	22.966***
	(219.313)	(2.610)	(6.791)
Size	–5.294**	–0.003	0.014
	(2.161)	(0.012)	(0.043)
Capital	0.458	–0.020***	–0.018*
	(0.307)	(0.002)	(0.011)
Liquidity	0.550***	–0.002***	0.007***
	(0.096)	(0.001)	(0.002)
NIIshare	0.159***	0.003***	0.005***
	(0.050)	(0.001)	(0.002)
GDP	1.937*	–0.144***	0.264***
	(1.076)	(0.021)	(0.040)
Refinancing rates	–2.149***	0.033***	0.122***
	(0.287)	(0.003)	(0.010)
Crisis	38.239***	0.000	0.092
	(3.604)	(0.000)	(0.083)
COVID-19	0.892	–0.455***	1.273***
	(4.521)	(0.087)	(0.163)
Observations	356	387	387
Banks	31	31	31

Notes: The table reports the results for the effect of earnings opacity on bank development as captured by the volume, quality, and costs of bank credit. The dependent variables are displayed at the head of each column. All columns are estimated by the LSDVC estimator. Bootstrapped standard errors are presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

Table 10. Robustness checks with shocking periods excluded

	Financial crisis excluded			COVID-19 excluded			Financial crisis and COVID-19 excluded		
	(1) LGR	(2) LLR	(3) NIM	(4) LGR	(5) LLR	(6) NIM	(7) LGR	(8) LLR	(9) NIM
Lagged LGR	0.360***			0.279***			0.344***		
	(0.019)			(0.020)			(0.022)		
Lagged LLR		0.538***			0.520***			0.558***	
		(0.030)			(0.029)			(0.031)	
Lagged NIM			0.684***			0.596***			0.690***
			(0.039)			(0.037)			(0.042)
Opacity	1,535.210***	9.992***	19.761***	1,206.402***	10.426***	19.220***	1,442.153***	9.777***	26.252***
	(202.461)	(1.420)	(6.413)	(217.945)	(1.523)	(2.613)	(200.596)	(1.583)	(3.113)
Size	–6.853***	–0.004	0.053	–5.083***	0.009	–0.008	–7.150***	–0.012	–0.040*
	(0.843)	(0.010)	(0.066)	(1.231)	(0.013)	(0.021)	(1.297)	(0.011)	(0.022)
Capital	–0.361	–0.021***	–0.016	0.268	–0.019***	–0.012*	–0.189	–0.021***	–0.032***
	(0.239)	(0.002)	(0.018)	(0.355)	(0.002)	(0.006)	(0.363)	(0.002)	(0.009)
Liquidity	0.518***	–0.001	0.011***	0.486***	–0.001**	0.006***	0.556***	–0.001	0.008***
	(0.074)	(0.001)	(0.002)	(0.090)	(0.001)	(0.002)	(0.080)	(0.001)	(0.003)
NIIshare	0.306***	0.003***	0.005**	0.233***	0.003***	0.004*	0.300***	0.003***	0.007***
	(0.045)	(0.001)	(0.002)	(0.033)	(0.001)	(0.002)	(0.042)	(0.001)	(0.002)
GDP	–4.306***	–0.102***	0.231***	1.309	–0.129***	0.236***	–4.235***	–0.102***	0.229***
	(1.063)	(0.019)	(0.030)	(1.064)	(0.018)	(0.028)	(1.014)	(0.018)	(0.020)
Refinancing rates	–2.674***	0.032***	0.101***	–1.632***	0.036***	0.111***	–2.671***	0.032***	0.107***
	(0.170)	(0.003)	(0.008)	(0.241)	(0.003)	(0.009)	(0.211)	(0.003)	(0.009)
COVID-19	–24.355***	–0.286***	1.093***						
	(4.725)	(0.079)	(0.133)						
Crisis				33.943***	–0.134***	0.002			
				(4.249)	(0.024)	(0.066)			
Observations	331	334	334	328	359	359	303	306	306
Banks	31	31	31	31	31	31	31	31	31
Instruments	28	28	28	28	28	28	27	27	27
AR(1) test (p-value)	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000
AR(2) test (p-value)	0.136	0.277	0.284	0.482	0.302	0.269	0.113	0.232	0.187
Hansen test (p-value)	0.403	0.331	0.477	0.187	0.260	0.183	0.206	0.131	0.280

Notes: The table reports the results for the effect of earnings opacity on bank development as captured by the volume, quality, and costs of bank credit. The dependent variables are displayed at the head of each column. All columns are estimated by the two-step system GMM estimator for the excluded-crisis sample (columns 1–3), excluded-pandemic sample (columns 4–6), and excluded-crisis-and-pandemic sample (columns 7–9). Standard errors are presented in parentheses. ***, **, and * represent statistical significance at 1%, 5%, and 10% levels, respectively.

5. Conclusion

This paper evaluates the impact of opaque financial reporting on bank development captured in the form of the quantity, quality, and costs of bank credit. Relying on a sample of commercial banks from Vietnam during 2007–2021, our research reveals three main patterns. First, greater bank opacity increases a bank's credit volume. Second, opaque financial reporting reduces the quality of bank credit. Third, earnings manipulations tend to increase the costs of bank lending. Overall, our robust evidence supports the view that greater bank opacity results in a large but inefficient (i.e., high cost) and unsafe banking sector.

Our paper suggests insightful policy implications. The findings show that opacity adversely affects the efficiency and safety of the banking sector, thereby weakening the long-term sustainability of the economy. Therefore, for the benefit of the market and the economy, tightened information disclosure requirements for the banking sector should be in place. For instance, banks have to be requested to pursue transparency and market disciplines as the third pillar of the Basel III framework. This is particularly true during the booming periods when making the banking system healthier and more efficient is necessary rather than chasing growth and expansion.

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