Navigate with Caution: The Unintended Consequences of ECL Adoption in Chinese Banks

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Abstract

The newly introduced Expected Credit Loss (ECL) model mandates banks to set aside loss provisions from the time a loan is originated, as opposed to only when there are imminent signals of loss. This suggests a limited scope for discretion by banks in managing these reserves. Using unique branch level enforcement action data and a proprietary population-location bank branch dataset, this study examines the impact of adopting the ECL model on bank non-compliance in China, focusing on enforcement actions and reasons. Our findings reveal that banks adopting the ECL model show a significant increase in non-compliance behaviors, particularly in loan release and real estate sectors. Additionally, cross-sectional analysis indicates that these effects are more pronounced in regions where governments have higher fiscal expenditures. We also observe unintended spillover effects, with non-ECL adopting bank branches being 43% more likely to receive fines and regulatory scrutiny if they are located within one kilometer of branches that have adopted the ECL model. This can be potentially explained by intensified competition among banks in the same region.

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"Adventure is the life of commerce, but caution is the life of banking." -- Walter Bagehot

1. Introduction

Loan loss provision is a critical component of bank accounting, representing an expense allocated as a reserve for potentially uncollectible loans. A key characteristic of loan loss provisioning is the considerable discretion banks have in determining the timing and amount of these provisions. This discretion has raised concerns among investors and regulators for several reasons. For instance, banks might set aside fewer provisions to inflate their income and capital (Moyer, 1990; Docking, Hirschey, and Jones, 1997; Ahmed, Takeda, and Thomas, 1999). During financial crises, such practice allows banks holding impaired assets to meet capital requirements, making it challenging to evaluate their actual financial status (Huizinga and Laeven, 2009). In response to these concerns, accounting standard setters have enhanced the standards and practices for loan loss provisioning. International Accounting Standards Board (IASB) released IFRS 9 Financial Instruments in 2014, introducing the "expected credit losses" (ECL) model. Similarly, the Financial Accounting Standards Board (FASB) introduced the "current expected credit losses" model in 2016. These updated standards were implemented between 2018 and 2021 within the IASB and FASB frameworks. [1]

The previously prevalent accounting approach is the “incurred credit loss” (ICL hereafter) model, which requires documentation of credit losses that have occurred by the balance sheet date. The identification of the ICL model relies on verifiable “triggering” events (e.g., borrower's job loss, collateral value decline, past-due status). The newly introduced approach is the Expected Credit Loss (ECL) model. This ECL model requires banks to reserve loss provisions from loan origination and does not wait for imminent loss signals. The shift from ICL to ECL represents a

[1] The IASB standard becomes compulsory for annual periods from 1 January 2018 onwards, with the option for earlier implementation. The FASB regulations will be implemented in 2020 for listed companies and in 2021 for other entities.

significant change in how banks account for potential loan losses, with implications for financial reporting, risk management, and regulatory compliance.

Loan loss provisioning is a crucial discretionary element in bank accounting, significantly influencing capital ratios and profitability (Bushman and Williams, 2012; Beatty and Liao, 2014; Ryan, 2017). The shift towards the Expected Credit Loss (ECL) model has garnered considerable attention from economists and policymakers due to its potential impacts on bank behavior and financial stability. Research demonstrates that adopting the forward-looking credit loss provisioning approach enhances the transparency and efficiency of bank information (Harris, Khan, and Nissim, 2018; Balakrishnan and Ertan, 2019; Espinosa, Ormazabal, and Sakasai, 2021; Kim et al., 2021), mitigating corruption and regulatory forbearance (Akins, Dou, and Ng, 2017; Wheeler, 2019). However, existing empirical studies on how adopting the ECL model influences bank risk-taking have yielded mixed results. On the one hand, the ECL model promotes banking discipline (Bushman and Williams, 2015; Granja, 2018; Bhat, Ryan, and Vyas, 2018; Ertan, 2019; Li, Ng, and Saffar, 2022). On the other hand[2], the ECL model has no significant constraint on bank's risk-taking behaviors (e.g., Jiménez et al., 2017; Ballew, Nicoletti, and Stuber, 2022; Illueca et al., 2022; Mahieux, Sapra, and Zhang, 2022).

Given the mixed evidence on the impact of the ECL model on bank risk-taking, our study aims to provide new insights by focusing on non-compliance behaviors[3]. Specifically, we address the following research questions: How does the adoption of the ECL model affect bank branch non-compliance behaviors? What is the relationship between timelier loan loss provisioning and

[2] Bushman and Williams (2012) suggest that smoothing earnings through early provisioning correlates to increased risk-taking, highlighting that discretional, prospective loss provisions could lead to unintended consequences.
[3] Our measures of bank non-compliance behavior are collected from the enforcement action letters provided by the China Banking and Insurance Regulatory Commission (CBIRC). Under the prudential capital requirements, regulators are responsible observe banks' compliance behavior and risk-taking to secure the safety and soundness of banks (BIS, 2017).

the frequency and severity of enforcement actions? How do local economic and political environments influence the impact of ECL adoption on bank non-compliance? What changes occur in the types of enforcement reasons following ECL adoption?

We find an unintended consequence that early recognized provisioning is associated with more enforcement actions and fine amounts. We further discover that although timelier loan loss provisioning reduces the bank's non-compliance in non-performing assets, banks conduct more non-compliance behaviors in loan issuance and real estate sector. We also observe spillover effects, with non-ECL adopting bank branches being 43% more likely to receive fines and regulatory scrutiny if located within one kilometer of branches that have adopted the ECL model. To the best of our knowledge, with a bank branch sample of over one million observations, our study is the first large evidence exploring bank non-compliance behavior in China.

2. Hypothesis development

Hypothesis I: The adoption of the Expected Credit Loss (ECL) model enhances banking compliance by requiring early loan loss provisioning, enabling banks to proactively assess and manage financial risks from loan origination.

The adoption of the Expected Credit Loss (ECL) model represents a significant shift in banking risk management practices, potentially enhancing overall compliance. This model requires banks to set aside provisions for potential loan losses from the moment of loan origination, rather than waiting for losses to become evident. Bushman and Williams (2012) highlight that banks implementing early provisioning for potential loan losses demonstrate stronger risk-taking discipline. This proactive approach enables banks to assess their financial health and risk exposures earlier in the loan lifecycle, fostering improved banking discipline and compliance.

Furthermore, the ECL model's emphasis on early recognition of potential losses enhances banks' capacity to manage and mitigate risks effectively. Studies by Bushman and Williams (2015), Ryan (2017), Chang et al. (2023), and Gallemore (2023) underscore that this early recognition reduces the likelihood of non-compliant behavior, as banks are better equipped to respond to emerging risks before they escalate. Consequently, the adoption of the ECL model promotes a more disciplined and proactive approach to compliance and risk management. Thus, we propose the risk-mitigating hypothesis, suggesting that the implementation of the ECL model leads to improved risk assessment and management practices, ultimately reducing the incidence of non-compliant behavior in the banking sector.

Hypothesis II: Early loan loss provisions deplete substantial capital, leading banks to engage in riskier lending practices to maintain profitability, thereby increasing the likelihood of non-compliance in loan issuance.

While early provisioning is generally seen as a prudent risk management practice, this hypothesis posits that the capital depletion caused by early loan loss provisions incentivizes banks to pursue higher-yield, higher-risk lending strategies. Jiménez et al. (2017) provide evidence that banks subject to earlier loan loss provisioning tend to lend to riskier borrowers at higher interest rates. Illueca et al. (2022) corroborate this finding, noting that in response to increased total loan loss provisions, banks have elevated the risk profile of their loan portfolios.

This phenomenon aligns with the broader concept of risk shifting in the literature on capital regulations and bank risk-taking. Studies by Koehn and Santomero (1980), Kim and Santomero (1988), Allen, Carletti, and Leonello (2011), and Berger and Bouwman (2013) suggest that banks may offset the stabilizing effects of increased capital requirements by seeking greater risks. Additionally, the concept of "loss overhang," where banks overestimate potential losses, can further deplete future capital reserves, exacerbating risk-taking behaviors (Bushman and Williams, 2015; Lu and Nikolaev, 2022). This paradoxical outcome suggests that measures intended to enhance financial stability may inadvertently drive banks towards more precarious lending strategies, potentially compromising the integrity of their loan portfolios and overall risk profile. Thus, while early provisioning aims to mitigate risk, it may paradoxically create a tension between prudential measures and profit-seeking behavior, potentially leading to an increased likelihood of non-compliance in loan issuance.

Hypothesis III: The implementation of the Expected Credit Loss (ECL) model, while limiting banks' discretion in reporting lower loan losses, may inadvertently incentivize false financial disclosures, thereby increasing the probability of non-compliance behavior in misreporting information.

The implementation of the Expected Credit Loss (ECL) model, while intended to enhance transparency in banking, may inadvertently create new incentives for non-compliance through misreporting. Bischof, Laux, and Leuz (2021) highlight that under the previously incurred credit loss model, banks exercised discretion to report lower loan losses. The ECL model is designed to limit this discretion and requires banks to periodically assess and disclose loan portfolio risks (PwC, 2017). However, this heightened transparency and increased capital requirement create a significant reporting burden, potentially incentivizing banks to provide false financial disclosures. This situation presents banks with a critical trade-off: they must weigh the advantage of manipulating financial statements against the cost of penalties if such misreporting is discovered. The pressure to meet ECL obligations may lead to an increase in non-compliance behavior, specifically in the form of financial misreporting. Consequently, while the ECL model aims to improve financial reporting accuracy, it may paradoxically increase the likelihood of non-compliance through false disclosures, obscuring the intended benefits of enhanced risk management and transparency. Hence, we label this hypothesis as the *(mis)reporting* motive. This (mis)reporting motive adds complexity to understanding the impact of ECL adoption on bank compliance, suggesting that the true effects must be empirically determined by considering the interplay between risk-mitigating, risk-shifting, and misreporting motivations.

3. Institutional background

We choose to investigate this issue in China as its banking sector is the largest in the world. The CBIRC oversees banks to comply with relevant laws and regulations. It performs on-site inspections and off-site tracking. This top-tier banking regulatory body possesses significant supervisory authority and is widely regarded as efficient. A 2017 International Monetary Fund report states that China's banking regulatory agency has "attained a substantial level of adherence to the Basel Core Principles for Effective Banking Supervision" (IMF, 2017).

China adopted the IFRS-based China Accounting Standards (CAS) in 2007 (IASB 2006). With the introduction of IFRS 9, the Chinese Ministry of Finance introduced CAS Numbers 22-24 on 31 March 2017. Specifically, CAS No. 22 facilitates transitioning from the ICL to ECL provisioning. This standard mandated its application starting 1 January 2018 for banks listed on stock exchanges offshore (such as Hong Kong stock exchanges), 1 January 2019 for banks listed domestically (such as Shanghai stock exchanges and Shenzhen stock exchanges), and 1 January 2021, for non-listed banks. Early adoption was restricted and only permitted if a bank's parent company or its subsidiaries were already listed or intended to be listed on stock exchanges where IFRS was required. The obligatory transition to Expected Credit Loss (ECL) provisioning, in line with the implementation of IFRS 9 Financial Instruments, marks a significant transformation in the banking sector (PBOC, 2018). This regulatory change offers a unique opportunity to test the role of loan loss provisioning on bank non-compliance.

4. Data, variables, and summary statistics

4.1. Data and sample construction

We collected 23,881 branch enforcement actions record from 2016 to 2022 on CBIRC website. We obtained a comprehensive bank branch dataset from CBIRC, which covers all bank branches in China. Specifically, this population dataset includes over 140,000 branches. For each branch, we observe the branch name, ID, hierarchy, and detailed address information. Since this dataset covers all bank branches in China, we can observe the full dynamics of individual branch non-compliance behaviors across the entire country.

The reform of CBIRC in 2015 moved the supervision for bank branches from central committee to city-level offices. Except for entry, exit, and reorganization, local offices take responsibility for supervising local bank branches. We collect city-level economic variables from the CEIC database to control for the cross-city heterogeneity in estimating the effects during our sample period. We perform textual analysis to classify the enforcement actions by the penalty reasons to further validate our hypothesis and discover the channel driving bank non-compliance behavior after adopting the ECL model. In Table 1, Panel A shows the variable definition of the outcome variable on penalties and city-level control variables. Panel B reports the number of penalty events by year. Panel C presents the number of penalty events by year.

4.2. Estimating the effects of the ECL model on bank non-compliance behavior

To test our hypothesis on the change in banks' non-compliance behavior after the mandatory shift in loan loss provisions, we employ a staggered difference-in-differences (DID hereafter) framework that compares changes in the number and penalty amount of enforcement actions for the ECL model-affected banks with the corresponding changes for the not-affected benchmark banks on the extensive margin. To wit, we separate banks that adopted the ECL model (treated banks) and banks that did not adopt the ECL model (control banks). The treated and control banks are classified before and after the time-varying adoption date of the ECL model between 2018 and 2021(i.e., January 1, 2018, for banks listed in Hong Kong Stock Exchanges; January 1, 2019, for banks listed in Shanghai and Shenzhen Stock Exchanges; January 1, 2021, for banks non-listed). If adopting the ECL model reduces bank's risk-taking, then the reduction in non-compliance behavior should be more pronounced in banks that adopt the ECL model. We estimate the staggered DID regression and the parallel trend analysis as follows:[4]

$$Y_{i,t} = \beta_1 PostECL_{i,t} + \Gamma Controls_{i,t} + \nu_i + \tau_t + e_{i,t} \quad , \tag{1}$$

$$Y_{i,t} = \beta_1 PostECL_{i,t} + \beta_2 PreECL_{i,t} + \nu_i + \tau_t + e_{i,t}, \tag{2}$$

where *i* and *t* denote the branch and year, respectively. *Y* is the outcome variable of enforcement actions on non-compliance behavior (*Penalty*), including the natural logarithm of the number of enforcement actions, fine amount, and further classifications on enforcement reasons. $PostECL_{i,t}$ is a binary variable that equals one if bank *i* has been mandated to adopt the ECL model as of year t. $PreECL$ is a binary variable that equals one if the current year *t* of branch *i* minus the branch's first year taking the ECL model < 0. $PostECL$ is a binary variable that equals one if the current year *t* of branch *i* minus the branch's first year taking the ECL model ≥ 0. In addition to including bank, city, and year fixed effects, we cluster standard errors at the bank level to assess the significance of regression coefficients.

[4] Following Hung et al (2023), we exclude early adopters to minimize the impact of unseen factors associated with the banks' decisions to adopt ECL and their provisioning strategies.

4.3. *Cross-sectional heterogeneity in results*

We examine various cross-sectional heterogeneities to further substantiate our hypothesis. In Eq. (3), we estimate Eq. (1) after adding a list of city characteristics (*Char*) and its interaction term with $PostECL_{i,t}$ to capture the cross-sectional heterogeneity associated with each hypothesis.

$$Y_{i,t} = \beta_1 PostECL_{i,t} + \beta_2 PostECL_{i,t} \times Char + \nu_i + \tau_t + e_{i,t}, \tag{3}$$

We study how the provision-compliance relation varies across banks depending on the local environment of the banking industry (supply-side factors) and political-economic conditions (demand-side factors). On the supply side, we use the total number of year-end deposits and loans of financial institutions (*deposit_inst*, *loan_inst*) to proxy for the level of local bank financing and earning capacity. For a bank operating in a financially constrained environment, the likelihood and magnitude of risky activities are negatively related to the bank's ability to finance (Lin and Paravisini, 2012). Banks have more incentives to apply an aggressive strategy when they are more subject to lower earning capacity (Fraisse, Lé, and Thesmar, 2020). Thus, if the risk-taking incentive plays an important role in shaping the positive relation between loan loss provisioning and bank non-compliance, we expect the results to be greater for banks with low ability to make deposits and loans. We also expect branches operating in a highly competitive market to be more willing to apply aggressive risk-taking strategies and have more non-compliance behaviors. We employ the total number of bank branches (*numberofbanks*) to proxy for the level of competition in the local banking industry. Evidence from worldwide and in China has shown that increased bank competition can bring negative consequences such as risk-taking (e.g., Keeley (1990); Allen and Gale (2000); Jiang, Levine, and Lin (2017); Gao et al. (2019)). A recent study by Carlson, Correia, and Luck (2022) documents that banks in markets with higher competition take more risks to meet capital requirements and have more defaults.

On the demand side, banks' willingness to conduct risk-taking activities should be affected by local economic and political conditions, which are often shaped by government fiscal needs and policies. We use the government expenses (*expense_gov*) to proxy for regulator willingness and anticipate it to be positively related to the level of local bank risk-taking. The regulators' willingness is related to the literature that governors promote incentives, impacting the banks' accounting strategies (Hung et al., 2023). The housing price in China has started to rise dramatically since 2015, and banks may be involved in the housing boom.[5] We control the total amount of real estate investments (*inv_real*) to proxy for the risk from the property market. We use the logarithm of GDP (*GDP*) to represent local economic development.

4.4. Estimate the geographic spillover effects

Given the time-varying implementation of the ECL model, we use the geographical coordinates data from Gao, Ru, and Yang (2022) to explore the spillover effect from banks that already take ECL to banks that do not in the same year and city[6]. We measure inter-bank geographic proximity in Eq. (3) by calculating the spherical distance formula proposed by Coval and Moskowitz (1999):

$$D_{i,t} = R \times arccos\ [sin(Bank_m Lat) \times sin(Bank_n Lat) + cos(Bank_m Lat) \times cos(Bank_n Lat) \times cos(Bank_m Lon - Bank_n Lon)], \tag{4}$$

where $\mathrm{Bank_m Lat}$ and $\mathrm{Bank}_n\mathrm{Lat}$ are the latitudes of the branch that does not take ECL (bank *m*), and the branch that takes ECL (bank *n*), respectively. $\mathrm{Bank}_m\mathrm{Lon}$ and $\mathrm{Bank}_n\mathrm{Lon}$ are the longitudes of bank *m* and bank *n* locations respectively. R is the radius of the earth (i.e., 6,378 kilometers). The latitude and longitude numbers are converted into radians by division by 180/π.

[5] Nearly 40 percent of all bank loans are related to property in China and property market losses can expose asset risks to banks through non-performing loans (Bloomberg, 2023).

[6] Gao, Ru, and Yang (2022) utilize GIS technology to pinpoint the precise longitude and latitude (four-digit latitudes and longitudes) of every bank branch on the map.

Banks usually have multiple branches in a city. We follow previous studies and choose the shortest one (i.e., the distance between branches from banks does not take ECL to the closest banks that take ECL in a given city) as the spillover distance. In total, there are over 300,000 spillover observations at the branch-year level.

$$Y_{i,t} = \beta_1 PostECL_{i,t} + \beta_2 PostSpillover_{i,t} + \nu_i + \tau_t + e_{i,t}, \tag{5}$$

In Eq. (4), *PostSpillover* is a dummy that equals one if the branch does not take ECL and gets spillover by the branch taking ECL within *D* kilometers distance. We test a list of distances from 0.1 to 10 kilometers to ensure our results are robust.

4.5. Summary statistics

Table 2 reports the summary statistics for the variables used in Eq. (2). All continuous variables are calculated by log (x+1) and winsorized at the 5% level in both tails of their distributions to mitigate the effects of outliers. Panel A presents the distribution of the number of enforcement actions by city level, branch level, and bank type. Panel B shows the distribution of the total fine amount imposed by enforcement actions at the city level, at the branch level, and by bank type. We find substantial variation in the levels of non-compliance among banks across different regions, hierarchies, and types. The mean *Penalty_n* in the prefectural city is 0.012, approximately 1.7 times as large as that of the corresponding value in the municipal city. The mean *Penalty_n* of the central branch is 0.166, indicating that for an individual bank, most enforcement actions are on the central branch. Based on the bank types, we find that state-owned banks have the lowest mean number of enforcement actions. The mean *Penalty_c* of joint equity banks is 0.069, which is significantly higher than other commercial banks.

5. Main results

5.1. The baseline results

Table 3 presents the parallel trend analysis of our staggered DID approach. The standard errors of the estimated coefficients are clustered at the bank level. We use different combinations of fixed effects and add control variables. The coefficient on *PreECL* is not significant and shows no pre-trend prior to the adoption of the ECL model. Table 4 presents our baseline regression results. In column (1), the coefficient of *PostECL* on *penalty_n* is positive and significant at the 5% level (coefficient = 0.0012, t-statistic = 2.11). In column (5), the coefficient of *PostECL* on *penalty_n* is positive and significant at the 10% level (coefficient = 0.0039, t-statistic = 2.03), suggesting an unintended consequence that Chinese banks, on average, become more aggressive by recognizing loan loss provisions in a timelier manner. This result supports the risk-shifting channel that adopting the ECL model incentivises banks' to pursue greater risks and more non-compliance behaviors. However, this can also be explained by the alternative hypothesis that adopting the ECL model dampens banks' incentives to disclose losses and leads to more enforcement actions regarding financial statement fraud.

Hence, we further test the adoption of ECL for enforcement reasons to explore whether our baseline results are driven by the alternative motive. We classify bank non-compliance behaviors into six categories: Internal Control (*internal_control)*, Loan Release (*loan_release)*, Risk Management (*risk_management),* Real Estate Assets (*real_estate),* Non-performing Loans (*NPL*), and Fraud Statements (*fraud_statement)*. To conserve space, we conduct these tests with the control variables and add bank*city and year fixed effects. Table 5 presents the results. In column (7), we find the measure on fraud statements is zero and not significant, which erases the alternative explanation for the increase of bank non-compliance behaviors in our baseline regressions. The estimate for internal control is 0.0002, which is also not significant.

More importantly, in column (10), we find the estimate of *Risk Management* is 0.004 and not significant, but the coefficient of *Extend Loan* in column (4) is significantly positive at the 5% level (coefficient = 0.0008, t-statistic = 2.12). This result supports the risk-shifting hypothesis and is consistent with Illueca et al., (2022). Furthermore, in column (13), we also find the estimate on *Real Estate* is significantly positive at the 5% level (coefficient = 0.0003, t-statistic = 2.30), implying that banks are experiencing more non-compliance behavior from the real estate sector. In column (16), the estimate on *NPL* is significantly negative at the 5% level (coefficient = -0.0002, t-statistic = -2.46), indicating the ECL model positively reduces bank non-performing loans by increasing the timeliness of loss recognition rather than awaiting for imminent loss signals.

Collectively, our results in Table 4 and Table 5 suggest that adopting the ECL model has a positive association with banks' non-compliance, consistent with the risk-shifting hypothesis that banks increase their loan portfolio risk in response to the decreased overall bank financial risk brought by timelier loan loss provisioning. This positive association is both statistically and economically significant. We also find evidence that the expansion of the real estate sector has a positive impact on bank non-compliance during our sample period.

5.2. Cross-sectional heterogeneity in results

We combine the ECL adoption effect with city-level characteristics. The results presented in Table 6 show that the coefficients of GDP are significantly positive with the number and fine amount of non-compliance activities, suggesting that those non-compliance behaviors are more likely to be concentrated in big cities. The financial institutions' year-end deposit balance is significantly negative with the number and fine amount of non-compliance activities. We interpret this finding as evidence of the local banking sector's financing capacity. The estimateon total number of local banks is significantly negative. This can be explained that competition promotes bank compliance. Moreover, the government expenditure is positively significant. This validates our prediction that regulator willingness is positively related to the level of local bank risk-taking. The coefficient of *inv_real* is significantly negative, indicating that property market losses or government fiscal needs are not the leading cause of bank non-compliance behavior.

5.3. The geographical spillover effect

Table 7 examines the effects of adopting the Expected Credit Loss (ECL) model and its geographic spillover on enforcement actions and fines. The analysis reveals that banks adopting the ECL model (*PostECL*) see significant increases in both the number of enforcement actions (*penalty_n*) and the fine amounts (*penalty_c*). For instance, a coefficient of 0.0109 for *penalty_n* at 1 km spillover distance implies a 1.09% increase in enforcement actions post-ECL adoption, indicating heightened regulatory scrutiny or challenges in compliance. The significant coefficients for *penalty_c*, such as 0.0422, suggest that adopting banks face higher fines. In 2018, many of these banks were bigger banks such as state-owned banks, which might have influenced their strategic decisions and become more aggressive after implementing the ECL model.

Interestingly, the spillover effects (*PostSpillover*) are also significant, with non-ECL adopting branches experiencing substantial increases in enforcement actions and fines. For example, the coefficient for *penalty_n* reaches 0.0156 at 1 km spillover distance, suggesting a 1.56% increase in enforcement actions. Compared with the ECL-adopting branches, these non-ECL-adopting branches are 43% more likely to receive regulatory penalties. This unintended spillover effect can also be attributed to competitive pressures in the banking sector, where smaller banks, which were not initially mandated to adopt the ECL model, felt compelled to adopt more aggressive strategies to remain competitive. This is further evidenced by the even higher coefficients for *penalty_c* in the spillover context, such as 0.0558, indicating that fines are more significant for these non-ECL banks, possibly due to their aggressive tactics or increased risk exposure.

Control variables like GDP show positive coefficients, such as 0.0063 for *penalty_n*, indicating that banks in wealthier regions may face more enforcement actions, possibly due to more complex financial activities or stricter regulatory environments. Conversely, the negative coefficients for *loan_inst*, like -0.0039, suggest that banks with larger loan portfolios may face fewer penalties, potentially due to better risk management practices. Overall, the findings highlight how regulatory changes and market dynamics can significantly impact bank behavior and regulatory outcomes, with implications for both policymakers and banking strategy.

6. Conclusion

The newly introduced Expected Credit Loss (ECL) model mandates banks to set aside loss provisions from the time a loan is originated, as opposed to only when there are imminent signals of loss. This suggests a limited scope for discretion by banks in managing these reserves. In this paper, we explore the impact of modifications to the ECL model on banks' non-compliance behavior. Employing a staggered Difference-in-Differences (DID) approach, our findings reveal an intriguing paradox: the adoption of the Expected Credit Loss (ECL) model, which was anticipated to bolster banking discipline by facilitating the early identification of credit losses, appears to have counterintuitively precipitated an uptick in non-compliance behaviors among banks. This unintended effect can be explained by the risk-shifting hypothesis that banks shift risks to loan portfolios to maintain profitability. The results might also be explained by the alternative hypothesis on misreporting, which suggests that the ECL model incentivizes banks to manipulate financial statements, thereby exacerbating non-compliance activities.

To conclude, the adoption of the ECL model has led to an increase in non-compliance behaviors among Chinese banks, with significant effects observed in the loan release and real estate sectors. The study also identifies spillover effects, indicating that non-ECL adopting bank branches are 43% more likely to receive fines and regulatory scrutiny if they are located within 1 km of branches that have adopted the ECL model. These findings highlight the need for regulators to consider the broader implications of new accounting standards and their potential to induce riskier behavior in the banking sector.

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Table 1. Variable Definitions

Panel A shows the variable definition of the outcome variable on penalties and city-level control variables. All variables are calculated by log (x+1). Panel B reports the number of penalty events by year. Panel C presents the number of penalty events by year.

Panel A: Variable definitions

Variable	Definitions	Obs	Mean	Std. dev.
penalty_n	Number of enforcement actions	1,031,022	0.011	0.109
penalty_c	Fine amount of enforcement actions	1,031,022	0.040	0.394
internal_control	Branch internal monitoring: related transaction, embezzlement etc.	1,031,022	0.004	0.095
loan_release	Branch loan release	1,031,022	0.011	0.163
risk_management	Branch risk management	1,031,022	0.009	0.146
real_estate	Branch real estate non-compliance	1,031,022	0.002	0.060
non_performing	Branch non-performing assets	1,031,022	0.001	0.035
statement_fraud	Branch statement fraud: conceal loss, inflate income, shift cost etc.	1,031,022	0.004	0.093
inv_real	City real estate investment	1,025,536	6.077	1.405
gdp	City gross domestic product	1,030,380	8.251	1.135
expense_gov	City government expenditure	1,030,141	6.512	0.953
deposit_inst	City financial institutions' year-end deposit balance	1,030,116	8.799	1.345
loan_inst	City financial institutions' year-end loan balance	1,030,116	8.515	1.425
numberofbanks	City number of total branches	1,031,022	7.083	0.776

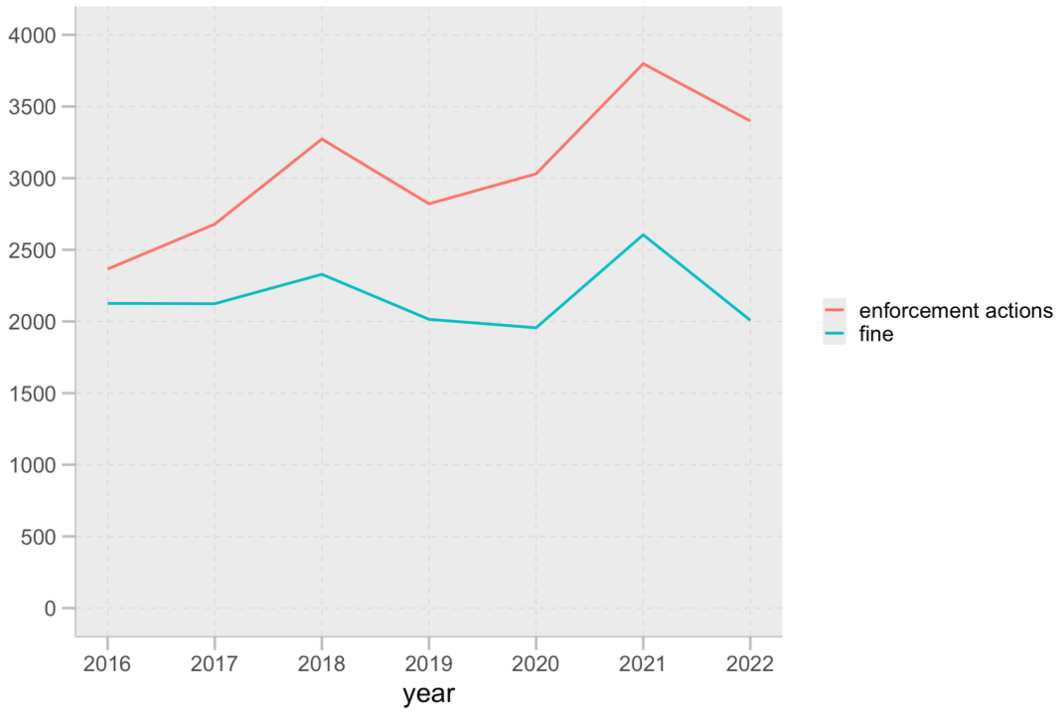
Panel B: Number of enforcement action(s)

Year	Number = 0	1	2	3	4	5	6	7	8	Total
2016	137,890	1,458	206	63	34	17	8	2	3	139,681
2017	141,497	1,162	277	104	63	38	12	15	4	143,172
2018	144,541	1,036	356	158	103	50	31	21	7	146,303
2019	147,304	945	316	125	73	39	31	12	14	148,859
2020	149,422	900	313	161	94	45	39	14	11	150,999
2021	148,977	1,129	476	203	109	57	29	18	11	151,009
2022	149,292	873	407	209	111	44	34	15	14	150,999
Total	1,018,923	7,503	2,351	1,023	587	290	184	97	64	1,031,022

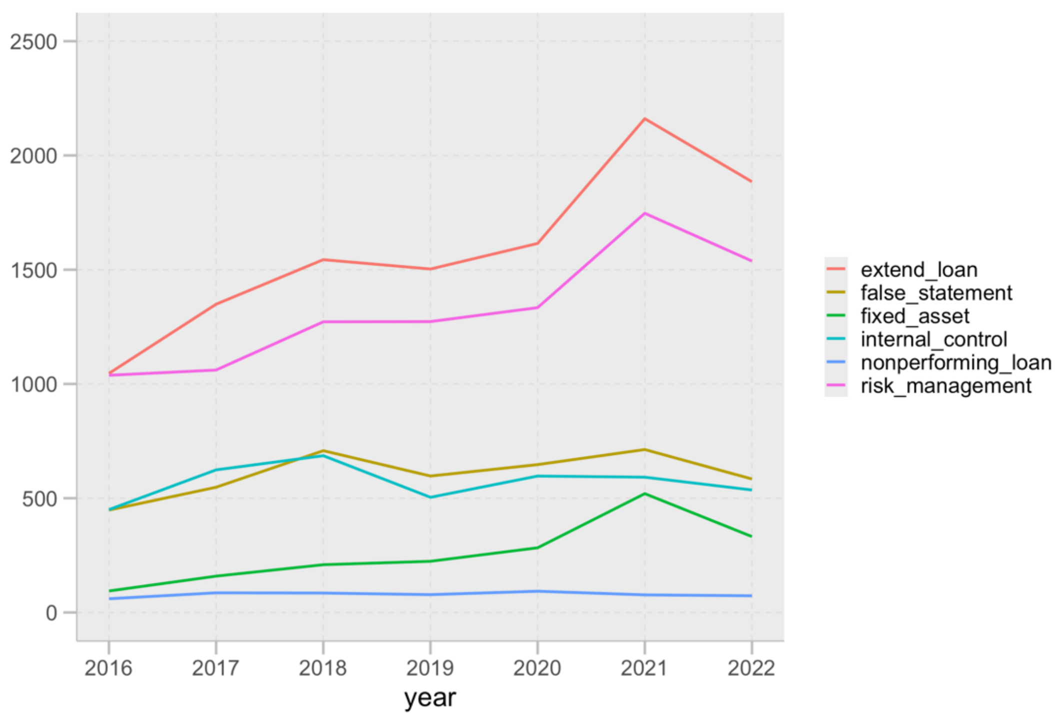
Panel C: Number of fine events in enforcement actions

Year	Number = 0	1	2	3	4	5	6	7	8	Total
2016	137,961	1,449	187	52	18	11	2	0	1	139,681
2017	141,585	1,259	208	65	33	15	2	5	0	143,172
2018	144,653	1,241	262	70	47	19	6	5	0	146,303
2019	147,396	1124	220	58	36	18	6	1	0	148,859
2020	149,594	1078	205	65	31	11	12	2	1	150,999
2021	149,105	1,461	291	88	38	16	5	4	1	151,009
2022	149,498	1141	259	68	24	6	2	1	0	150,999
Total	1,019,792	8,753	1,632	466	227	96	35	18	3	1,031,022

Figure 1. The enforcement actions and reasons



(a) Number of enforcement actions



(b) Number of enforcement reasons

Table 2. Summary Statistics

Panel A presents the distribution of the number of enforcement actions by city level, branch level, and bank type. Panel B shows the distribution of the total monetary penalties imposed by enforcement actions at the city level, at the branch level, and by bank type.

Panel A: Distribution of the number of enforcement actions Y = log (penalty_n + 1)				
City level	Obs	Mean	Std. dev.	Max
Municipal city	82,368	0.007	0.081	2.197
Vice-provincial city	135,549	0.009	0.094	2.197
Autonomous city	81,784	0.011	0.113	2.197
Prefectural city	731,321	0.012	0.113	2.197
Branch level	Obs	Mean	Std. dev.	Max
Sub-branch	958,510	0.003	0.053	2.197
Second-level branch	24,944	0.084	0.279	2.197
First-level branch	17,611	0.105	0.312	2.197
Central branch	23,707	0.166	0.406	2.197
Bank type	Obs	Mean	Std. dev.	Max
State-owned bank	475,011	0.006	0.079	2.197
Rural commercial bank	281,041	0.012	0.116	2.197
Foreign bank	5,848	0.010	0.088	1.609
City commercial bank	111,235	0.013	0.119	2.197
Policy bank	15,494	0.014	0.118	2.079
Joint equity bank	93,725	0.016	0.126	2.197
Village bank	38,979	0.025	0.163	2.197
Rural credit bank	5,459	0.149	0.396	2.197
Private bank	119	0.149	0.391	2.079
Panel B: Distribution of the fine amount of enforcement actions Y = log (penalty_c + 1)				
City level	Obs	Mean	Std. dev.	Max
Municipal city	82,368	0.034	0.403	10.860
Vice-provincial city	135,549	0.036	0.384	11.187
Autonomous city	81,784	0.039	0.390	10.057
Prefecturel city	731,321	0.042	0.395	9.775
Branch level	Obs	Mean	Std. dev.	Max
Sub-branch	958,510	0.008	0.169	8.987
Second-level branch	24,944	0.329	1.052	9.088
First-level branch	17,611	0.449	1.290	10.745
Central branch	23,707	0.622	1.465	11.187
Bank type	Obs	Mean	Std. dev.	Max
State-owned bank	475,011	0.023	0.295	10.860
Rural commercial bank	281,041	0.038	0.379	9.690

Foreign bank	5,848	0.051	0.461	7.022
City commercial bank	111,235	0.051	0.449	8.456
Policy bank	15,494	0.056	0.457	8.902
Joint equity bank	93,725	0.069	0.533	11.187
Village bank	38,979	0.086	0.552	6.787
Rural credit bank	5,459	0.511	1.301	7.431
Private bank	119	0.695	1.762	6.962

Table 3. Parallel trend analysis

The sample consists of listed and non-listed banks in the Hong Kong, Shanghai, and Shenzhen Stock Exchanges. The adoption of the ECL model starts on 1 January 2018 for banks listed on foreign stock exchanges (such as those in Hong Kong), 1 January 2019 for domestic banks (such as those in Shanghai and Shenzhen), and 1 January 2021 for non-listed banks. *Before1* is a binary variable that equals one if the current year *t* of branch *i* minus the branch's first year taking ECL = -1. After0 is a binary variable that equals one if the current year *t* of branch *i* minus the branch's first year taking ECL = 0. After1+ is a binary variable that equals one if the current year *t* of branch *i* minus the branch's first year taking ECL ≥ 1. Columns (3), (4), (7), (8) include the control variables described in Table 1, but their coefficients are not tabulated. Bank, city, bank*city, and year fixed effect are included. The standard errors of the estimated coefficients are clustered at the bank level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y=	*penalty_n*	*penalty_n*	*penalty_n*	*penalty_n*	*penalty_c*	*penalty_c*	*penalty_c*	*penalty_c*
Pre1	-0.0002	-0.0002	-0.0002	-0.0001	-0.0029	-0.0026	-0.0026	-0.0025
	(-0.41)	(-0.26)	(-0.31)	(-0.22)	(-1.48)	(-1.31)	(-1.34)	(-1.24)
Post0	0.0005	0.0005	0.0006	0.0005	0.0000	-0.0000	0.0001	-0.0001
	(0.83)	(0.83)	(0.87)	(0.83)	(0.01)	(-0.02)	(0.05)	(-0.03)
Post1+	0.0018**	0.0018**	0.0018**	0.0018**	0.0056*	0.0057*	0.0054*	0.0055*
	(1.98)	(2.01)	(1.98)	(1.99)	(1.70)	(1.73)	(1.67)	(1.67)
inv_real			0.0006	0.0007			-0.0000	0.0001
			(0.93)	(0.96)			(-0.01)	(0.05)
gdp			0.0064***	0.0063***			0.0305***	0.0300***
			(3.25)	(3.21)			(4.10)	(4.05)
expense_gov			0.0014	0.0014			0.0042	0.0039
			(0.97)	(0.95)			(0.82)	(0.77)
deposit_inst			0.0024	0.0024			0.0112*	0.0109*
			(1.12)	(1.10)			(1.91)	(1.86)
loan_inst			-0.0037*	-0.0038**			-0.0200***	-0.0204***
			(-1.91)	(-1.97)			(-3.66)	(-3.73)
numberofbanks			-0.0114***	-0.0112***			-0.0317***	-0.0309***
			(-3.72)	(-3.63)			(-2.85)	(-2.76)
Bank FE	Yes		Yes		Yes		Yes	
Bank and City FE	Yes		Yes		Yes		Yes	
Bank*City FE		Yes		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,031,022	1,031,022	1,025,536	1,025,535	1,031,022	1,031,022	1,025,536	1,025,535
Adj. R-squared	0.0256	0.0348	0.0257	0.0349	0.0217	0.0299	0.0219	0.0301

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 4. The Adoption of the ECL model and enforcement actions

The sample consists of listed and non-listed banks in the Hong Kong, Shanghai, and Shenzhen Stock Exchanges. The adoption of the ECL model starts on 1 January 2018 for banks listed on foreign stock exchanges (such as those in Hong Kong), 1 January 2019 for domestic banks (such as those in Shanghai and Shenzhen), and 1 January 2021 for non-listed banks. $PostECL_{i,t}$ is a binary variable that equals one if bank i has been mandated to adopt the ECL model as of year t. *penalty_n* is the log value of one plus the number of enforcement actions, and *penalty_c* is the log value of one plus the fine amount of enforcement actions. Bank, city, bank*city, and year fixed effect are included. The standard errors of the estimated coefficients are clustered at the bank level.

	(1)	(2)	(3)	(4)	(5)	(7)	(6)	(8)
Y=	*penalty_n*	*penalty_n*	*penalty_n*	*penalty_n*	*penalty_c*	*penalty_c*	*penalty_c*	*penalty_c*
PostECL	0.0012**	0.0011**	0.0011**	0.0011**	0.0039**	0.0037*	0.0037*	0.0035*
	(2.11)	(2.04)	(2.06)	(1.98)	(2.03)	(1.94)	(1.95)	(1.85)
inv_real			0.0006	0.0006			-0.0003	-0.0002
			(0.87)	(0.90)			(-0.14)	(-0.08)
gdp			0.0064***	0.0063***			0.0308***	0.0302***
			(3.27)	(3.23)			(4.12)	(4.08)
expense_gov			0.0014	0.0014			0.0039	0.0036
			(0.95)	(0.93)			(0.77)	(0.72)
deposit_inst			0.0025	0.0025			0.0120**	0.0117**
			(1.18)	(1.17)			(2.07)	(2.01)
loan_inst			-0.0037*	-0.0039**			-0.0203***	-0.0208***
			(-1.95)	(-2.02)			(-3.75)	(-3.82)
numberofbanks			-0.0115***	-0.0113***			-0.0322***	-0.0313***
			(-3.71)	(-3.62)			(-2.86)	(-2.77)
Bank FE	Yes		Yes		Yes		Yes	
City FE	Yes		Yes		Yes		Yes	
Bank*City FE		Yes		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,031,022	1,031,022	1,025,536	1,025,535	1,031,022	1,031,022	1,025,536	1,025,535
Adj. R-squared	0.0256	0.0348	0.0257	0.0349	0.0217	0.0299	0.0219	0.0301

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 5. The adoption of the ECL model and enforcement reasons

The sample consists of listed and non-listed banks in the Hong Kong, Shanghai, and Shenzhen Stock Exchanges. The adoption of the ECL model starts on 1 January 2018 for banks listed on foreign stock exchanges (such as those in Hong Kong), 1 January 2019 for domestic banks (such as those in Shanghai and Shenzhen), and 1 January 2021 for non-listed banks. $PostECL_{i,t}$ is a binary variable that equals one if bank i has been mandated to adopt the ECL model as of year t. *Internal Control* is the log value of one plus the number of enforcement actions on internal control, and *Extend Loan* is the log value of one plus the number of enforcement actions on extending loans. *Fraud Statement* is the log value of one plus the number of enforcement actions on fraud statement. *Risk Management* is the log value of one plus the number of enforcement actions on risk management. *Real Estate* is the log value of one plus the number of enforcement actions on real estate assest. *NPL* is the log value of one plus the number of enforcement actions on non-performing loan. bank*city, and year fixed effect are included. The standard errors of the estimated coefficients are clustered at the bank level.

Y=	(1) *Internal Control*	(2) *Internal Control*	(3) *Internal Control*	(4) *Extending Loan*	(5) *Extending Loan*	(6) *Extending Loan*	(7) *Fraud Statement*	(8) *Fraud Statement*	(9) *Fraud Statement*
PostECL	0.0002	-0.0001		0.0008**	0.0008*		0.0000	0.0002	
	(1.17)	(-0.39)		(2.12)	(1.70)		(0.21)	(0.58)	
Post1+			-0.0004			0.0011*			0.0001
			(-1.49)			(1.73)			(0.34)
Post0			-0.0000			0.0007			0.0002
			(-0.18)			(1.58)			(0.59)
Pre1		-0.0005**	-0.0007***		-0.0001	0.0001		0.0002	0.0002
		(-2.11)	(-2.74)		(-0.19)	(0.14)		(0.72)	(0.65)
inv_real	-0.0001	-0.0001	-0.0001	0.0003	0.0003	0.0003	-0.0002	-0.0002	-0.0002
	(-0.37)	(-0.31)	(-0.35)	(0.62)	(0.63)	(0.64)	(-0.63)	(-0.64)	(-0.65)
gdp	0.0009	0.0009	0.0009	0.0030***	0.0030***	0.0030***	0.0012*	0.0012*	0.0012*
	(1.47)	(1.45)	(1.47)	(2.89)	(2.88)	(2.88)	(1.76)	(1.76)	(1.77)
expense_gov	-0.0003	-0.0002	-0.0002	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001	-0.0001
	(-0.37)	(-0.31)	(-0.31)	(-0.11)	(-0.11)	(-0.11)	(-0.09)	(-0.11)	(-0.11)
deposit_inst	-0.0001	-0.0002	-0.0002	0.0019	0.0019	0.0019	0.0020***	0.0020***	0.0020***
	(-0.12)	(-0.20)	(-0.19)	(1.23)	(1.22)	(1.21)	(2.95)	(2.99)	(2.99)
loan_inst	0.0003	0.0003	0.0003	-0.0007	-0.0007	-0.0007	-0.0013**	-0.0013**	-0.0013**
	(0.43)	(0.46)	(0.45)	(-0.47)	(-0.47)	(-0.46)	(-2.17)	(-2.19)	(-2.19)
numberofbanks	-0.0006	-0.0006	-0.0006	-0.0069***	-0.0069***	-0.0069***	-0.0027***	-0.0027***	-0.0027***
	(-0.50)	(-0.50)	(-0.52)	(-3.32)	(-3.32)	(-3.33)	(-2.75)	(-2.75)	(-2.76)
Bank*City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535
Adj. R-squared	0.0228	0.0228	0.0228	0.0327	0.0327	0.0327	0.0239	0.0239	0.0239

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Y=	(1) Risk Management	(2) Risk Management	(3) Risk Management	(4) Real Estate	(5) Real Estate	(6) Real Estate	(7) NPL	(8) NPL	(9) NPL
PostECL	0.0004	0.0003		0.0003**	0.0002		-0.0002**	-0.0002**	
	(1.16)	(0.80)		(2.30)	(1.49)		(-2.46)	(-2.17)	
Post1+			0.0005			0.0007***			-0.0002
			(0.89)			(3.24)			(-1.54)
Post0			0.0003			0.0002			-0.0002**
			(0.73)			(0.97)			(-2.21)
Pre1		-0.0001	-0.0000		-0.0001	0.0001		-0.0000	0.0000
		(-0.23)	(-0.01)		(-0.76)	(0.88)		(-0.02)	(0.12)
inv_real	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	-0.0000	-0.0000	-0.0000
	(0.31)	(0.31)	(0.32)	(1.05)	(1.06)	(1.13)	(-0.09)	(-0.09)	(-0.09)
gdp	0.0010	0.0010	0.0010	0.0010**	0.0010**	0.0010**	0.0006*	0.0006*	0.0006*
	(1.06)	(1.06)	(1.05)	(2.40)	(2.40)	(2.35)	(1.71)	(1.71)	(1.71)
expense_gov	0.0009	0.0009	0.0009	0.0002	0.0002	0.0002	-0.0001	-0.0001	-0.0001
	(0.88)	(0.89)	(0.88)	(0.37)	(0.38)	(0.37)	(-0.34)	(-0.34)	(-0.34)
deposit_inst	0.0033**	0.0033**	0.0033**	-0.0014**	-0.0014**	-0.0014**	0.0002	0.0002	0.0002
	(2.16)	(2.13)	(2.12)	(-2.03)	(-2.04)	(-2.05)	(0.51)	(0.51)	(0.50)
loan_inst	-0.0043***	-0.0043***	-0.0043***	0.0018***	0.0018***	0.0019***	0.0000	0.0000	0.0001
	(-2.79)	(-2.77)	(-2.77)	(4.18)	(4.19)	(4.21)	(0.17)	(0.17)	(0.17)
numberofbanks	-0.0048***	-0.0048***	-0.0047***	-0.0011	-0.0011	-0.0010	-0.0008**	-0.0008**	-0.0008**
	(-2.75)	(-2.75)	(-2.75)	(-1.36)	(-1.36)	(-1.30)	(-2.11)	(-2.11)	(-2.11)
Bank*City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535
Adj. R-squared	0.0309	0.0309	0.0309	0.0171	0.0171	0.0171	0.0268	0.0267	0.0267

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Cross-sectional heterogeneity

The sample consists of listed and non-listed banks in the Hong Kong, Shanghai, and Shenzhen Stock Exchanges. The adoption of the ECL model starts on 1 January 2018 for banks listed on foreign stock exchanges (such as those in Hong Kong), 1 January 2019 for domestic banks (such as those in Shanghai and Shenzhen), and 1 January 2021 for non-listed banks. $PostECL_{i,t}$ is a binary variable that equals one if bank i has been mandated to adopt the ECL model as of year t. *penalty_n* is the log value of one plus the number of enforcement actions, and *penalty_c* is the log value of one plus the fine amount of enforcement actions. Bank, city, bank*city, and year fixed effect are included. The standard errors of the estimated coefficients are clustered at the bank level.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Y=	*penalty_n*	*penalty_n*	*penalty_n*	*penalty_n*	*penalty_c*	*penalty_c*	*penalty_c*	*penalty_c*
PostECL	0.0074**	0.0094**	0.0070**	0.0086**	0.0232*	0.0222*	0.0253**	0.0231*
	(2.05)	(2.56)	(1.97)	(2.35)	(1.95)	(1.89)	(2.14)	(1.94)
PostECL*inv_real	-0.0025***	-0.0029***	-0.0030***	-0.0036***	-0.0080***	-0.0094***	-0.0084***	-0.0103***
	(-3.42)	(-3.79)	(-3.70)	(-4.21)	(-3.41)	(-3.72)	(-3.32)	(-3.85)
PostECL*gdp	0.0029**	0.0034***	0.0018	0.0022**	0.0121***	0.0151***	0.0064*	0.0097**
	(2.47)	(2.76)	(1.60)	(1.97)	(2.81)	(3.31)	(1.67)	(2.37)
PostECL*expense_gov	0.0050***	0.0061***	0.0049***	0.0059***	0.0137***	0.0164***	0.0136***	0.0161***
	(4.05)	(4.55)	(4.18)	(4.72)	(3.24)	(3.81)	(3.35)	(3.93)
PostECL*deposit_inst	-0.0023	-0.0023	-0.0028*	-0.0026*	-0.0054	-0.0043	-0.0088*	-0.0068
	(-1.40)	(-1.42)	(-1.79)	(-1.72)	(-1.06)	(-0.89)	(-1.66)	(-1.36)
PostECL*loan_inst	-0.0014	-0.0015	-0.0001	-0.0003	-0.0055	-0.0076**	-0.0002	-0.0028
	(-1.19)	(-1.53)	(-0.08)	(-0.28)	(-1.49)	(-2.37)	(-0.05)	(-0.73)
PostECL*numberofbank	-0.0023**	-0.0036***	-0.0011	-0.0024**	-0.0093***	-0.0127***	-0.0046	-0.0083**
	(-2.29)	(-3.19)	(-1.17)	(-2.24)	(-2.77)	(-3.56)	(-1.43)	(-2.43)
inv_real			0.0015*	0.0017**			0.0021	0.0028
			(1.89)	(2.32)			(0.88)	(1.26)
gdp			0.0062***	0.0057***			0.0294***	0.0267***
			(3.41)	(3.21)			(4.29)	(4.02)
expense_gov			0.0004	0.0003			0.0012	0.0010
			(0.28)	(0.16)			(0.23)	(0.19)
deposit_inst			0.0025	0.0018			0.0126**	0.0089
			(1.11)	(0.78)			(1.99)	(1.37)
loan_inst			-0.0011	-0.0004			-0.0128**	-0.0103*
			(-0.55)	(-0.23)			(-2.38)	(-1.93)
numberofbanks			-0.0150***	-0.0148***			-0.0424***	-0.0407***
			(-4.01)	(-3.90)			(-3.27)	(-3.13)
Bank FE	Yes		Yes		Yes		Yes	
City FE	Yes		Yes		Yes		Yes	
Bank*City FE		Yes		Yes		Yes		Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,025,536	1,025,535	1,025,536	1,025,535	1,025,536	1,025,535	1,025,536	1,025,535
Adj. R-squared	0.0258	0.0351	0.0258	0.0351	0.0219	0.0301	0.0220	0.0302

Robust t-statistics in parentheses

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 7. The spillover effects

The sample consists of listed and non-listed banks in the Hong Kong, Shanghai, and Shenzhen Stock Exchanges. The adoption of the ECL model starts on 1 January 2018 for banks listed on foreign stock exchanges (such as those in Hong Kong), 1 January 2019 for domestic banks (such as those in Shanghai and Shenzhen), and 1 January 2021 for non-listed banks. $PostECL_{i,t}$ is a binary variable that equals one if bank i has been mandated to adopt the ECL model as of year *t*. *penalty_n* is the log value of one plus the number of enforcement actions, and *penalty_c* is the log value of one plus the fine amount of enforcement actions. *PostSpillover* is a dummy that equals one if the branch does not take ECL gets spillover by the branch taking ECL within D kilometers distance. bank*city, and year fixed effect are included. The standard errors of the estimated coefficients are clustered at the bank level.

	D=0.1	*D=0.5*	*D=1*	*D=3*	*D=0.1*	*D=0.5*	*D=1*	*D=3*
Y=	*penalty_n*	*penalty_n*	*penalty_n*	*penalty_n*	*penalty_c*	*penalty_c*	*penalty_c*	*penalty_c*
PostECL	0.0022***	0.0086***	0.0109***	0.0125***	0.0071***	0.0287***	0.0365***	0.0422***
	(3.95)	(14.55)	(18.77)	(21.53)	(3.67)	(14.86)	(19.53)	(23.44)
PostSpillover	0.0056***	0.0142***	0.0156***	0.0165***	0.0178***	0.0476***	0.0524***	0.0558***
	(4.90)	(16.90)	(20.56)	(23.69)	(4.45)	(16.64)	(20.31)	(24.09)
inv_real	0.0006	0.0006	0.0006	0.0006	-0.0002	-0.0003	-0.0002	-0.0002
	(0.90)	(0.84)	(0.87)	(0.87)	(-0.09)	(-0.15)	(-0.12)	(-0.11)
gdp	0.0063***	0.0063***	0.0063***	0.0062***	0.0302***	0.0301***	0.0301***	0.0300***
	(3.22)	(3.22)	(3.22)	(3.21)	(4.07)	(4.08)	(4.07)	(4.07)
expense_gov	0.0014	0.0015	0.0016	0.0017	0.0037	0.0042	0.0044	0.0048
	(0.96)	(1.03)	(1.08)	(1.14)	(0.74)	(0.82)	(0.86)	(0.93)
deposit_inst	0.0025	0.0026	0.0025	0.0025	0.0118**	0.0120**	0.0118**	0.0118**
	(1.18)	(1.21)	(1.18)	(1.18)	(2.02)	(2.06)	(2.03)	(2.03)
loan_inst	-0.0039**	-0.0039**	-0.0039**	-0.0039**	-0.0209***	-0.0210***	-0.0209***	-0.0208***
	(-2.04)	(-2.05)	(-2.04)	(-2.03)	(-3.84)	(-3.86)	(-3.84)	(-3.83)
numberofbanks	-0.0113***	-0.0111***	-0.0110***	-0.0109***	-0.0312***	-0.0306***	-0.0304***	-0.0301***
	(-3.62)	(-3.59)	(-3.57)	(-3.55)	(-2.77)	(-2.73)	(-2.71)	(-2.68)
Bank*City FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535	1,025,535
Adj. R-squared	0.0350	0.0356	0.0357	0.0357	0.0301	0.0306	0.0307	0.0307

Robust t-statistics in parentheses

*** p<0.01, ** p<0.05, * p<0.1