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Capital Market Discipline and Bank Credit Risk: The Role of Bank Ownership Structure

By *Berat Bayram, Mustafa Çelik, Abdullah Kazdal, Yavuz Kılıç, Faruk Yücel Özcan, Muhammed Hasan Yılmaz*

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The Role of Bank Ownership Structure

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Abstract

This study investigates the link between capital market discipline and bank-level credit risk with a special emphasis on the role of bank ownership structure. Focusing on a large emerging market, Turkey, characterized by prominent state bank presence, our baseline regression results indicate that banks' stock price volatility elevates in response to the increases in non-performing loan ratio for the period 2008-2021. More importantly, the extent of capital market discipline on credit risk is amplified for state-owned banks. This finding remains similar against a myriad of robustness checks. To analyze the implications on alternative financial markets, we further extract high-frequency implied volatility measures from options contracts recently traded on individual bank stocks. By utilizing the Covid-19 outbreak as an exogenous shock to local banks' loan portfolio quality, we perform difference-in-differences estimations for the interval October 2019-June 2020. Our findings show that the implied volatility for non-private banks increases more in the post-shock phase compared to other bank ownership types.

JEL Codes: G21, G14, G32, C50

Keywords: Stock Price Volatility, Credit Risk, Option-Implied Volatility

1. Introduction and Related Literature

Excessive risk-taking behavior coupled with inadequate monitoring and regulation schemes has been identified as a major factor causing bank vulnerabilities during the Global Financial Crisis (GFC) (Fortin et al., 2010). GFC had drastic implications on banking industry dynamics, including capital buffers (Acharya et al., 2011); lending (Kapan and Minoiu, 2018); capital inflows (Hoggarth et al., 2010); loan interest rates (Hristov et al., 2014), as well as financing opportunities for firms and households (Demirgüç-Kunt et al., 2020). Hence, in the post-crisis episode, policymakers initiated a broad reform agenda for banking regulation emphasizing the controlling mechanisms facilitated by bank outsiders.

As an example of such mechanisms, Flannery (2001) conceptualizes market discipline as the ability of financial markets to analyze firm riskiness to alter pricing tendencies accordingly. It is commonly argued that if market discipline works well, the likelihood of excessive bank risk-taking would be lowered (Nier and Baumann, 2006). The concept of market discipline was previously proposed by Basel Committee on Banking Supervision (BCBS) under the Basel II framework involving enhanced bank transparency and information sharing to facilitate the evaluation of bank soundness by market participants (Godspower-Akpomiemie and Ojah, 2021). The consequent wave of regulations aiming to contain excessive bank risk and prevent bank insolvency also emphasizes on the role of external monitoring (Dermine, 2013; Thakor, 2018).[1]

Banks have inherently unique characteristics aggravating agency problems, inducing excessive risk-taking behavior and, accordingly, requiring a greater necessity for external discipline. First and foremost, unlike non-financial firms, banking companies are highly levered. Although bank shareholders contribute a lower share in bank funding, they hold residual claims over bank assets and have the maximum control over the determination of bank policies. Such a corporate formation naturally yields an excessive conflict between shareholders and debtholders in following risky activities (Hagendorff, 2019). Moreover, in contrast to real sector firms, banks in most countries operate under implicit and explicit

[1] Basel III framework initiated by BCBS further maintained market discipline as one of the main pillars of bank regulation (Flannery and Bliss, 2019). As a comprehensive reformation of financial architecture in the US, the Dodd-Frank Wall Street Reform and Consumer Protection Act of 2010 directly aimed to improve market discipline (Balasubramnian and Cyree, 2014).

deposit insurance reducing the effectiveness of monitoring imposed by outsiders (Anginer et al., 2014). Banks provide vital intermediation services for the functioning of real economic activities (Berger et al., 2020). Therefore, following any financial failure with system-wide disturbance, banking firms are most likely to receive bailouts and provisional funds which incapacitate external discipline (Cubillas et al., 2012). Hence, analyzing the relevance of the market discipline to banking firms holds importance from financial stability and policymaking perspectives.

Prior works analyze how the effectiveness of market discipline varies depending on debt-capital mix in bank funding structure (Ashcraft, 2008); bank size (Bertay et al., 2013); regulatory changes (Balasubramnian and Cyree, 2014); uninsured liabilities (Nier and Baumann, 2006); shareholder control (Forssbæck, 2011); Islamic banking practices (Aysan et al., 2017); bank creditors (Bennett et al., 2015) and deposit insurance scheme (Calomiris and Jaremski, 2019).

In this paper, we focus on the ownership structure and how it influences the external market discipline for banks. Specifically, we investigate how the response of stock price volatility to bank credit risk varies based on state ownership of banks. Compared to other bank types, state banks are unique entities in terms of corporate governance, organizational purpose, the existence of implicit financial safety nets and relationships with respect to different bank stakeholders. Although the regulatory and supervisory scrutiny tend to be similar with private banks, these factors could interact with external capital market discipline and investor perception. To present empirical evidence, we utilize a sample of publicly traded Turkish banks for the period 2008-2021 by constructing bank-level stock market price volatility indicators from equity market data. Establishing empirical design in this way also allows us to analyze the role of state ownership in a detailed way since state banks historically carry considerable market share in the domestic banking industry of Turkey. Besides, using Turkish banks equips us to capture variation in bank risk at high frequency via accessing the regulatory database maintained by the Central Bank of Turkey (CBRT) in the form of monthly financial statements.

Our baseline regressions document that stock price volatility raises as a response to an elevation in bank credit risk, while this relationship is found to be amplified for state banks.

Baseline findings are robust to a myriad of robustness checks, alternative stock price volatility indicators, and credit risk evolution across different sub-segments of loans.

To extend our empirical analysis, in subsequent estimations, we utilize volatility measures derived from options markets. On the grounds that bank-level option contracts data has only been vastly available for the latter parts of the sample period in the context of Turkey, we utilize the recent Covid-19 outbreak in a quasi-experimental setting. In this context, we consider the emergence of the pandemic as an exogenous shock to domestic banks' loan quality to investigate the change in option-implied volatility of state and non-state banks from pre- to post-pandemic period. The difference-in-differences (DiD) estimation results with weekly data show that the non-private bank ownership amplifies how derivative market pricing reacts to bank risk. The main findings of these extended estimations are also validated by a variety of DiD model diagnostics, including the parallel trends assumption.

Our intended contribution to existing literature has three pillars. First, we provide additional empirical evidence concerning the role of direct state participation on banking sector outcomes. A well-developed group of research reveals the influence of state presence on the bank performance (Berger et al., 2005); efficiency of bank operations (Hou et al., 2013); risk-taking and prudent lending behavior (Angkinand and Wihlborg, 2010); deposit pricing (Mondschean and Opiela, 1999); lending growth (Bertay et al., 2015); accounting conservatism and bank opacity (Yue et al., 2021); loan contracting (Haß et al., 2019) and bank payout policy (Onali et al., 2016). We extend this branch of studies by analyzing how bank credit risk is perceived by capital markets in the case of state participation to banking industry.

Second, we try to further elaborate on discipline mechanisms in the context of banking industry. In terms of channels limiting the bank risk, prior discussion had primarily been centered on the regulatory and prudential oversight (Acharya, 2009; Laeven and Levine, 2009); institutional reforms (Fang et al., 2014); depositors (Berger and Turk-Ariss, 2015); subordinated debtholders (Godspower-Akpomiemie and Ojah, 2021) as well as internal corporate governance mechanisms including audit committee (Sun and Liu, 2014); board formation and structure (Dupire et al., 2021); managerial compensation design (Srivastav and Hagendorff, 2016) and stakeholder orientation (Leung et al., 2019). Notwithstanding, the direct empirical evidence regarding market discipline imposed by equity markets is relatively scarce for banking firms. The informative nature of equity markets for financial intermediaries has also been investigated by studies like Bliss and Flannery (2002), Curry et al. (2008), Francis et al. (2015), for which we try to contribute to.

The third pillar is related to growing literature assessing the implications of the recent Covid-19 outbreak on the banking industry outlook. Due to its sudden and devastating impact on economic and financial relationships, recent papers opt to utilize the Covid-19 pandemic as an exogenous variation in their empirical designs (Berger and Demirgüç-Kunt, 2021). To exemplify this impact, some empirical studies investigate the banking industry dynamics during the pandemic with respect to bank performance (Demirgüç-Kunt et al., 2021); financial stability (Elnahas et al., 2021); lending growth (Çolak and Öztekin, 2021) and liquidity supply (Li et al., 2020). With our extended empirical analysis incorporating the Covid-19 phase as an exogenous shock to the credit risk of domestic banks in Turkey, we aim to advance this stream of literature. Specifically, we try to attain new empirical evidence relevant to market implied volatility of banks following the outbreak by using data of a large emerging economy.

The rest of the paper is ordered as follows. Section 2 conducts a further literature review to develop testable hypotheses. Section 3 describes the data and sample formation process. Section 4 explains the methodological setting. Section 5 presents baseline empirical findings, robustness checks and DiD analysis, whereas the last section provides concluding remarks.

2. Hypothesis Development

A particular group of studies suggests that direct state ownership could mitigate the risk perceptions of capital market participants. Banks controlled by state entities typically benefit from the existence of implicit and explicit guarantees more, alleviating the potential concerns in the case of insolvency (Faccio et al., 2006; Hryckiewicz, 2014). Iannotta et al. (2013) find that the market-implied probability of default tends to be lower for state-owned banks. Compared to private banks, Wang et al. (2018) document that state-owned banks contribute less to the interconnectedness during volatility shocks. State banks are also expected to experience less intense deposit withdrawals and more recapitalization efforts in the case of failure, which might assuage negative assessment by market participants (Brei and Schclarek, 2015).

Another strand of the literature hints at potential factors eliciting amplifying effect of state ownership on the capital market risk assessments. Unlike private counterparties focusing on profit-maximization, state banks have a unique corporate purpose of stabilizing the credit markets (against financial and macroeconomic disturbances) allowing them to internalize the benefits of lending practices. This behavior is particularly evident across downturn phases of the business cycle (and crisis episodes) when private and foreign banks tend to engage in credit rationing, whereas state-owned financial intermediaries are prone to sustain less pro-cyclical loan growth (Micco and Panizza, 2006; Bertay et al., 2015). Besides the short-term stabilization role, the development view in the literature posits that state bank lending is further motivated to provide funding to key industries, regions and firms to facilitate economic development in the long run, especially for financial systems with prominent bank financing (Gerschenkron, 1962; Cull et al., 2018). Furthermore, the social view in the literature argues that the ability of state bank lending to solve market failures has welfare-enhancing implications (Stiglitz, 1993; Cull et al., 2018).

However, the aforementioned desirable functions of state bank lending may inevitably result in lower profitability and higher operational risks (Sapienza, 2002; Micco et al., 2007; Cornett et al., 2010; Shaban and James, 2018). In terms of operational efficiency and prudential lending, prior studies document that foreign ownership schemes and privatization improve bank solvency and performance (Ianotta et al., 2007; Jiang et al., 2013; Shaban and James, 2018). The conventional asset quality ratios also display less pro-cyclical tendencies against macroeconomic fluctuations which diminishes the informativeness of bank reporting to reflect underlying credit risk. Lastly, state banks might be more influenced by agency issues and external conjuncture (Micco and Panizza, 2006; Coleman and Feler, 2015; Cai et al., 2017; Bircan and Saka, 2021). Hence, the direct state ownership might amplify the reaction of capital market participants' perceptions to bank credit risk.

Given the aforementioned lines of reasoning asserting that the direct participation of state in banking industry may either alleviate or amplify the capital market discipline against credit risk, two competing hypotheses can be formulated as follows:

H1A: *The response of market pricing volatility to credit risk is expected to be weaker for state-owned banks relative to private banks.*

H1B: *The response of market pricing volatility to credit risk is expected to be amplified for state-owned banks relative to private banks.*

3. Data

Data of banking firms' stock prices, retrieved from Bloomberg Terminal, is the main input for the construction of volatility proxies. We create our sample by utilizing financial market information of seven Turkish banks which are quoted to Borsa Istanbul (BIST) for the period May 2008-July 2021. As a large emerging market shaped by a bank-dependent financial system coincided with considerable state presence in financial intermediation activities, Turkey provides a suitable framework for empirically analyzing the role of direct state ownership.[2] Particularly, as of 2021, state banks manage 37% of total assets, extend 38% of total loans and collect 40% of total deposits in the Turkish banking industry.[3] The beginning of the sample period is determined by data availability, while the coverage of sample interval also equips us to include the GFC and recent Covid-19 outbreak as periods witnessing prominent volatilities in domestic financial markets.

According to the regulatory classification of Banking Regulation and Supervision Agency (BRSA), the majority of the ownership structure of two sample banks is controlled by the state entities. In this study, we follow the regulatory criteria in deciding the ownership status. In other words, we can retrieve non-missing market data for seven publicly traded banks during our sample period, two of which are designated as state banks by the BRSA. After obtaining individual banks' stock prices at daily frequency, we calculate the volatility indicators and convert them into monthly frequency by taking the end-of-month values to match them with the balance sheet information of banks.

We supplement financial data with additional information of bank-level credit risk through a balance sheet data set of Turkish banks which is made available by the Central Bank of the Republic of Turkey (CBRT). This information allows us to monitor the loan quality

[2] Besides, working with a single-country setting allows us to minimize the potential concerns stemming from confounders.

[3] In terms of segment classification, state banks allocate 42% of total retail loans, whilst they provide 37% of total commercial loans. Considering the fact that the payments for state employees and pensioners are facilitated by state banks, they hold a 45% share in total TL-denominated deposits. This number realizes at a 36% level for FX-denominated deposits.

outlook of Turkish banks at monthly frequency via the non-performing loans. The non-performing portion of the loan portfolio is defined as the sum of balances due 90 days or more and non-accruing balances. Besides credit risk, to construct other control variables, we collect additional monthly data regarding capital position, deposit funding base, investments in short-term securities, and the size of bank operations from the CBRT database. As additional controls measuring market microstructure dynamics, we extract bank-level financial data relevant to market capitalization, price-to-earnings ratio and stock return beta from Bloomberg Terminal.

In terms of the implications of market-based disciplining forces via options market pricing, we also construct implied volatility proxies based on option contracts traded on bank stocks in BIST, which gained depth in terms of market liquidity in the post-2017 period. The input for calculating weekly implied volatility indicators (to be used in subsequent DiD analysis) is retrieved from BIST Derivatives Market (VIOP) Bulletin. European-type single stock options are offered in VIOP.[4] Due to data limitations about the trading of the option contracts, we are able to work with a shortened version of our bank list involving five sample banks, two of which are still retained as stated-owned.

4. Methodology

Our empirical framework is designed with baseline regressions investigating the association between stock price volatility and bank credit risk, as well as how this relationship is subject to variation based on state ownership of banks. To this end, the following empirical specification is employed:

$$Volatility_{it} = \alpha + \beta_1 NPL\ Ratio_{it} + \beta_2 (NPL\ Ratio_{it}\ x\ State_i) + \gamma X_{it-1} + \rho_i + \delta_t + \varepsilon_{it} \quad (1)$$

where $Volatility_{it}$ is the dependent variable approximated by stock price volatility indicators representing the extent to which pricing of bank stocks is subject to fluctuations. The core independent variable, $NPL\ Ratio_{it}$, is the ratio of non-performing loans to total

[4] Maturity of the options is available regarding the end of the current contract month and the next two calendar months. Therefore, there are three different maturities for each trading day. Minimum 8 contracts, including one at-the-money, one in-the-money, and six out-of-money, are offered, and the number of contracts increases as the price fluctuates.

loans. The main variable of interest is the interaction term ($NPL\ Ratio_{it}\ x\ State_i$), comprising the multiplication of credit risk variable with a binary indicator taking the value of one for banks with direct state ownership, otherwise assuming the value of zero. The coefficient β_2 is monitored to identify the differential impact of state bank status on the relationship between stock price volatility and loan quality. ε_{it} stands for the stochastic error term. We utilize three different stock price volatility measures in the baseline case: $Close\ Close$, $Parkinson$ and $Garman\ Klass$ (please see Appendix A for detailed definitions).

Our regression model specified in equation (1) includes bank fixed effects (ρ_i) to control for time-invariant bank-level heterogeneities. The inclusion of month fixed effects (δ_t) aims to account for time-varying dynamics. Month fixed effects are specifically added to remove the calendar-based seasonality commonly observed in stock markets (Mills and Andrew Coutts, 1995; Marquering et al., 2006). X_{it-1} symbolizes the vector of other controls. In line with prior empirical studies, we augment bank-level control variables to the model including the ratio of equity to assets, the ratio of deposits to assets, the ratio of securities to assets and the natural logarithm of total assets (Konishi and Yashuda, 2004; Stiroh, 2006; Leung et al., 2015; Jankensgård and Wilhelmsson, 2016, Vo, 2016). To insulate the potential effects of market microstructure factors, we further add bank-level financial controls such as logarithm of market capitalization, logarithm of price-to-earnings ratio and individual stock return $Beta$ (Chen et al., 2006; Gatev et al., 2007; Pathan, 2009) (please see Appendix A for detailed definitions).

The aforementioned supplementary control variables are lagged for one period to alleviate possible simultaneity concerns. All continuous series are winsorized at 1st and 99th percentiles to minimize the impact of outliers. Detailed variable definitions and summary statistics are presented in Tables 1 and 2, respectively. Heteroscedasticity-robust standard errors are considered for inference.

$$[\boldsymbol{Insert\ Table\ 1\ Here}]$$

$$[\boldsymbol{Insert\ Table\ 2\ Here}]$$

5. Empirical Results

5.1. Baseline Results

The main estimation results are given in Table 3. Column (1) provides findings relevant to the simplified model predicting the dependent variable $Close\ Close$, whereas column (2) describes the estimation results of saturated model specification with other control variables. In both cases, the coefficient attached to the interaction term is positive and significant at the 1% level. Thus, baseline empirical analysis renders support to hypothesis (H1B) given that the state ownership of banks seems to amplify the link between credit risk embedded in the bank loan portfolio and pricing volatility observed in capital markets.

Columns (3) and (4) of Table 3 demonstrate estimation results when the alternative indicator $Parkinson$ is utilized as the dependent variable. The significant and positive coefficient taken from the interaction term further indicate the differential capital market disciplining observed for state-owned banks. Lastly, columns (5) and (6) repeat similar estimations for the dependent variable $Garman\ Klass$, whereas the interaction term is still found to be positive and highly significant.

With respect to other controls, findings are in line with prior literature and expectations (Delis and Kouretas, 2011; Agoraki et al., 2011; Kasman and Kasman, 2016; Altunbaş et al., 2017). The banks with sizeable holdings of securities in total asset base ($Securities$) experience stronger stock price volatility. Given that short-term marketable securities are prone to additional interest rate, market price, counterparty and liquidity risks, the banks investing heavily on those asset items might be perceived riskier by the investors. $Bank\ Size$ is negatively correlated with stock price volatility. This could be explained from the perspective that larger banks might be more capable of performing better risk management and hedging activities, consequently diminishing the investor concerns related to overall bank risk and resulting in subdued stock price volatility. In terms of market microstructure factors, $P/E\ Ratio$ is negatively correlated with stock volatility hinting that the banks with better prospects might be less inclined to excessive risk assessment in stock markets. Moreover, the variable $Beta$ has a positive and significant coefficient confirming that the individual banks' exposure to systematic risk is expected to compound the risk valuation performed by investors.

$[Insert\ Table\ 3\ Here]$

5.2. Additional Analyses and Robustness Checks

In this section, we discuss the analyses and diagnostics performed to strengthen the credibility of our baseline findings (Table 4). State banks and banks with other ownership types are expected to differ based on observable and unobservable characteristics that simultaneously influence market pricing and bank risk. The incapability of the baseline regression model to account for such omitted factors and systematic differences could complicate the inference process. Besides, state and non-state bank classification could be subject to covariate imbalance. To mitigate endogeneity concerns and potential covariate imbalance, we utilize the entropy balancing approach outlined by Hainmueller (2012) which is a re-weighting scheme applied to the pre-processing of units in a binary treatment observational study with the intent that the moments of covariate distributions are identical across treatment and re-weighted control group. In this context, we use the set of bank balance sheet features and consider the balancing constraint of first moment to obtain the weights. Panel (A) demonstrates the estimation results based on entropy-balanced sample which highlights that baseline findings remain similar as the interaction coefficients are positive and significant.

Furthermore, we return to the original (unweighted) sample and undertake a myriad of robustness checks related to data handling and modeling choices. In panel (B) of Table 4, we collect an alternative measure of credit risk from the regulatory database as the ratio of stage 2 loans to total loans ($Stage\ 2\ Loan\ Ratio$) and replace the main independent variable ($NPL\ Ratio$) as well as the interaction term in the specification. The balances placed under the Stage 2 classification are “closely-monitored” loans that have not been formally defaulted yet but are expected to become non-performing in the upcoming periods with higher probability. In other words, loans for which repayment is delayed for 30-90 days period are classified as closely monitored loans (i.e., second group). With the recent transition to the TFRS-9 reporting framework in Turkey, in addition to impaired loans, loans that are not impaired but are found to have “a significant increase in credit risk” according to in-house risk assessment models also began to be classified as closely monitored loans (CBRT, 2019). The incremental impact of state ownership is also significant when asset quality is proxied by $Stage\ 2\ Loan\ Ratio$.

Additionally, we replace the main independent variable ($NPL\ Ratio$) and the interaction term with another forward-looking measure of credit risk outlook. Particularly, we define the ratio of loan loss provisions to total loans ($Loan\ Loss\ Provisions\ Ratio$) and augment the specification in equation (1). Banks tend to set aside this income statement account for potential future loan defaults and expenses to accurately display the financial solvency. In this way, we could deduct banks' own ex-ante assessment of loan quality in upcoming periods. In panel (C), we find that the interaction term generated with the aforementioned ratio is still significantly positive.

In panel (D), we again turn our attention to baseline model specification but utilize two-way clustered standard errors instead of robust versions. In this context, clustering is done to control for possible correlations across both bank and time dimensions. We still observe the significance of baseline results with this clustering technique.[5] In panel (E), we drop individual fixed effects and saturate the model with higher degree (bank-by-month) fixed effects to account for time-varying bank-level forces. This exercise does not create any significant deviation from baseline findings. In panel (F), we repeat the estimations with raw data series negating any winsorization procedure. This set of results show that the implementation of data winsorization does not introduce any spurious effect on baseline findings. In panel (G), we use 3 months-lagged values of control variables, whilst main findings stay robust to this alternative modeling choice.

In the next part of robustness checks, we alter the data frequency to quarterly level to alleviate any concerns due to the frequency of audit reports' (and accompanying financial statements') publication schedule. In panel (H), we transform the data by taking end-of-quarter values and repeat the baseline specification by incorporating bank and quarter fixed effects. In panel (I), we follow an alternative procedure for data transformation via quarterly

[5] In untabulated set of results, we also obtain estimations with standard errors clustered at bank-type level based on ownership structure. We thank an anonymous reviewer for this comment. Additionally, we implement bootstrapping technique to retrieve standard errors. Main findings are intact to these extensions.

averages. In both cases, the interaction terms are positive and significant documenting the inflating role of bank ownership structure on capital market discipline.[6]

The extent of capital market reaction to credit risk dynamics could be spuriously driven by the mechanical changes in the loan portfolio composition instead of the influence of bank ownership structure. To ease such concerns, we use additional data from regulatory database and form the variables dynamically describing the share of commercial loans and FX-denominated loans in total loan portfolio. In panel (J), we extend the equation (1) by incorporating these controls and re-rerun the regressions. We observe that main inferences do not diverge once we control for other loan portfolio characteristics.[7]

$$[\textit{Insert Table 4 Here}]$$

Our regulatory dataset is granular enough to assess the validity of baseline relationships regarding the asset quality of various loan breakdowns so we are able to create monthly $NPL\ Ratio$ measures for credit sub-categories including consumer and commercial loans. In this context, we construct credit risk indicators for housing loans, credit cards, general-purpose loans, small and medium enterprise (SME) loans and micro-firm loans to repeat the estimations (Table 5). In panels (A) and (B), we observe that state ownership intensifies the implications of the asset quality of housing loans and credit card portfolios on market pricing volatility. When we consider credit risk in general-purpose loans (which are mainly used by households to finance short-term consumption activities such as purchase of durable goods), the relationship is reversed in the sense that the coefficient of the interaction term is negative (panel C). It shows that, for this particular loan type, the state ownership actually attenuates the negative perception and excessive pricing volatility in capital markets stemming from elevation in credit risk.[8] Furthermore, panels (D) and (E) focus on specific segments of commercial loans which are known to carry considerable credit and default risk traditionally. We find that in the case of both SME loans and loans extend to micro-

[6] We thank an anonymous reviewer for pointing out this issue.
[7] We thank an anonymous reviewer for pointing out this issue.
[8] It can be argued that the restructuring practices specific to general-purpose loans might play a role in the results relevant to this loan segment. State banks in Turkey mostly offer an opportunity to restructure the overdue general-purpose loans and personal credit card debts. Restructuring efforts might reduce the NPL ratio performing loan balances of state banks by smoothing the credit risk over time. This practice can be perceived by capital market participants as an implicit factor limiting the risk-taking behavior of state-owned financial intermediaries, in turn, supporting the heterogeneous relationship regarding the general-purpose loan segment.

enterprises, the state presence magnifies the reflection of asset quality assessments in stock market price formations.

$[\boldsymbol{Insert\ Table\ 5\ Here}]$

To ensure that the composition of dependent variables is not influential in the main relationships, we re-estimate the baseline model with alternative dependent variables by including same set of controls and fixed effects. Roger and Satchell (1991) incorporate a drift term and provide a more efficient volatility estimator when the drift of an underlying asset is not equal to zero. Yang and Zhang (2000) improve this estimator by incorporating the price gap between trading sessions. Alternatively, we define Value at Risk (VaR) as a risk measure indicating the maximum loss level on an investment over a given period with a certain confidence level. However, it is not a coherent risk measure given that four axioms (monotonicity, translation invariance, homogeneity and sub-additivity) should be satisfied for this measure to be fully coherent (Hull, 2012). Hence, as a further modification to the indicator formation, Conditional Value at Risk ($CVaR$), or expected shortfall, measures the expected loss exceeding VaR, given an arbitrary threshold (please see Appendix A for detailed definitions).

Columns (1) and (2) of Table 6 provide estimation results when $Roger\ Satchell$ and $Yang\ Zhang$ volatility proxies are employed as dependent variables. In both cases, the coefficient of the interaction term $NPL\ Ratio\ x\ State$ is positive and significant. Moreover, columns (3) and (4) consider VaR and $CVaR$ measures. This set of estimations also yields a similar conclusion asserting the amplifying impact of state ownership through a positive and significant interaction coefficient.

$[\boldsymbol{Insert\ Table\ 6\ Here}]$

5.3. Difference-in-Differences Analysis

The stock market is not the only platform by which the market disciplining forces can be monitored for domestic banks. To expand our empirical analysis, we extract implied volatility measures from option contracts traded on individual bank stocks at higher frequency. Historical volatility is considered as a backward-looking approach while implied volatility is forward-looking and estimates the future volatility of an underlying asset. Hence, publicly available data incorporated in the implied volatility could better describe the market expectations. Unfortunately, given that derivative markets in Turkey is recently developed in terms of clearinghouse services, standardization of instruments, central trading and market liquidity, viable option-implied volatility measures can be only produced for the recent period and a narrower set of banks.

In this section, with respect to implied volatility indicators, we perform a DiD estimation by using the recent Covid-19 outbreak as an exogenous shock to domestic financial stability in the Turkish banking industry. By exploiting the quasi-experimental design provided by the occurrence of the Covid-19 pandemic, we aim to make additional inferences regarding the role of state ownership on the connection between bank insolvency risk and domestic financial market volatility. In this case, the shock produced by the Covid-19 pandemic is plausibly exogenous to an individual emerging market setting (like Turkey) in the sense that neither credit risk dynamics of local banking industry nor pricing tendencies in domestic financial markets initiate the disturbance caused by the health crisis or accompanying economic/financial implications on a global scale due to travel restrictions, lockdowns and unprecedented drop in global trade and production. Besides, as argued by Çolak and Öztekin (2021) and Berger and Demirgüç-Kunt (2021), the Covid-19 outbreak can serve as a credible shock in banking research with DiD frameworks given that it created unanticipated and widespread pressure on financial intermediation activities worldwide. More relevant to our case, Elnahass et al. (2021) find that the asset quality of banks was subject to prominent deterioration in the wake of this health crisis and the following developments.

Similar to this line of research, we formulate our DiD specification as follows with the weekly data covering the interval October 2019-June 2020:

$$Option - Implied\ Volatility_{it} = \beta_1 Post_t + \beta_2 (Post_t\ x\ State_i) + \gamma X_{it} + \rho_i + \delta_t + \varepsilon_{it} \qquad (2)$$

In equation (2), the dependent variable is $Option - Implied\ Volatility_{it}$ is the implied volatility measure retrieved from traded option contracts written on individual bank stocks. The traded options in VIOP have the last business day of months as maturity. The technique highlighted by Dumas et al. (1998) is employed to derive one-month implied volatility measures (please see Appendix A for detailed definitions).

$Post_t$ is the shock variable taking value of the one aftermath the occurrence of Covid-19 outbreak, specifically following the third week of February 2020.[9] $State_i$ is the treatment variable taking the value of one for state-owned banks, otherwise assuming the value of zero. The coefficient of interest (β_2) is attached to DiD interaction term $Post_t \ x \ State_i$ quantifying the differential change in option-implied volatility of state banks from pre- to post-Covid outbreak period relative to privately-owned banks. In equation (9), we also control for the bank (ρ_i) and week (δ_t) fixed effects. This model specification further embodies a limited set of bank-level controls (X_{it}) which can be tracked at weekly frequency involving market capitalization, price-to-earnings ratio and individual stock return beta (due to data availability). ε_{it} stands for the stochastic error term.

Main DiD estimation results are provided in Table 7. In column (1), we exploit plain specification excluding other bank-level market microstructure controls, while column (2) focuses on the saturated model. In both columns, the coefficient on DiD interaction term is positive and significant. This reinforces the idea that the volatility of high-frequency pricing observed in the derivatives market following the exogenous disturbance to asset quality stays prevalent among state-owned banks compared to non-state counterparties.

$[\boldsymbol{Insert\ Table\ 7\ Here}]$

The applicability of DiD design is contingent upon the assumption that, prior to the shock, the outcome variable for treatment (state banks) and control (non-state banks) group is required to evolve in a similar course. To support the validity of parallel trends assumption in our framework, we perform additional analysis. In the first step, we undertake a visual analysis by depicting the average implied volatility measures for state and non-state bank groups. In Figure B1 of the Appendix B, average volatility series are scattered with a normalization based on the beginning of the sample value to identify the underlying trends. As evident in this figure, option-implied volatility proxies hover around similar trends in the

[9] In the mentioned period, as the number of cases increased for the first time in China with the effect of the pandemic, economic activity indicators, especially PMI and industrial production, plummeted to historically low levels, which led to a decline onset in the global economic activity. Likewise, relevant to the reaction of global financial markets, the volatility index (VIX) started to increase in this period while the risk appetite in financial markets began to diminish. As of this period, with the pandemic spreading worldwide, factories and workplaces were shut down, domestic and international travel was restricted, and quarantine measures were introduced. In the ongoing process, as the pandemic affected other countries, global trade and economic activity continued to weaken, and an almost unprecedented level of decline was seen in financial markets.

pre-shock period and begin to follow differential trends only after the occurrence of the Covid-19 outbreak. In the second analysis, we drop the post-treatment observations and create momentum indicators for volatility measures by taking the first difference throughout the pre-treatment episode. Then, we conduct a univariate t-test to assess the similarity of mean momentum indicators across state and non-state banks. Estimations results provided in Table B1 of the Appendix B validate the argument that both bank types follow a similar trend in the pre-shock phase.

As the third step to support the validity of our DiD design, we conduct placebo tests. In the first test, we keep the assignment of state bank status as well as the length of quasi-experimental setting same but we utilize data from 2017 to randomize the timing of shock. When we repeat the specification in equation (9) with placebo timing, as expected, we obtain insignificant results for DiD interaction term rendering further support to our inference (Table B2 of the Appendix B). In the scope of second placebo test, we keep the sample period same but we randomize the state bank status across individual bank observations by reshuffling the assignment of $State_i$ and performing estimations with pseudo treatment variable. We repeat this procedure 2000 times to record the distribution of placebo coefficients attached to DiD interaction term. Table B3 of the Appendix B provides percentile values of the aforementioned empirical distribution. The actual DiD impact seems to stay outside the interval of 5^{th} and 95^{th} percentile thresholds retrieved from placebo assignments. Thus, this placebo exercise further reinforces the argument that our DiD findings are not affected by randomness.[10]

6. Conclusion

In this study, we attempt to elaborate on one of the most important external discipline mechanisms for banking firms shaped by equity markets. We analyze how capital market monitoring interacts with direct state ownership participation of bank governance. By using a high-frequency regulatory data describing the course of the credit risk of quoted Turkish banks and stock return volatility measures derived from market pricing tendencies, we find that when banks operate with a higher level of default risk, they are more likely to be subject to

[10] Moreover, we utilize DiD analysis with event study by estimating dynamic treatment effects which also reinforces the validity of parallel trends assumption in our case. We thank an anonymous reviewer for the suggestion.

volatile stock returns. Interestingly, this discipline mechanism is found to be amplified for state-owned banks compared to banks with other ownership types.

Moreover, we show that our results remain similar against a myriad of robustness checks. The baseline finding stays same when we incorporate alternative definitions for the composition of dependent variables. The segment-wise analysis further yields the conclusion that the amplification caused by state ownership is evident in sub-categories of loans involving credit cards, housing, SME and micro-firm loans.

To analyze the pricing tendencies of market participants in a more detailed way with input from derivative markets, we also conduct DiD estimations utilizing the recent Covid-19 outbreak as a negative shock to bank loan portfolio quality combined with implied volatility measures derived from the options market as an outcome variable. These estimations confirm that unique bank ownership structure may lead to a stronger reaction from market participants as a response to the elevation of credit risk. Overall, our findings provide valuable information to regulators and investors by validating that the ownership structure is an influential determinant of how capital markets tend to price bank risk.

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Table 1: Variable Definitions

Variables	Definition	Source
Close Close	Volatility estimator, only closing prices	Bloomberg, Authors' Calculations
Parkinson	Volatility estimator, highest and lowest prices	Bloomberg, Authors' Calculations
Garman Klass	Volatility estimator, highest, lowest, opening and closing prices	Bloomberg, Authors' Calculations
NPL Ratio	The ratio of non-performing loans to total loans	CBRT
State	A binary indicator taking value of one for banks with majority state ownership, otherwise taking the value of zero	BRSA
Capital	The ratio of capital equity to total assets	CBRT
Deposits	The ratio of deposits to total assets	CBRT
Securities	The ratio of securities held to total assets	CBRT
Bank Size	Natural logarithm of total assets	CBRT
Market Cap	Natural logarithm of total market capitalization	Bloomberg
P/E Ratio	Natural logarithm of price to earnings ratio	Bloomberg
Beta	Measure of systematic risk	Bloomberg, Authors' Calculations

Note: This table presents detailed definitions and data sources of dependent and independent variables used in the main empirical analysis specified in equation (1).

Table 2: Summary Statistics

Variables	Obs.	Mean	Std. Dev.	Median	P10	P90
Dependent Variables						
Close Close	1,113	0.4018	0.1144	0.3750	0.2844	0.5887
Parkinson	1,113	0.3625	0.0997	0.3386	0.2582	0.5083
Garman Klass	1,113	0.4845	0.1315	0.4512	0.3459	0.6826
Control Variables						
NPL Ratio	1,113	0.0578	0.0222	0.0538	0.0331	0.0847
Capital	1,113	0.1581	0.0220	0.1523	0.1349	0.1879
Deposits	1,113	0.5231	0.0826	0.5176	0.4236	0.6387
Securities	1,113	0.2003	0.0772	0.1858	0.1184	0.3121
Bank Size	1,113	17.7636	1.4950	18.2019	15.1523	18.2863
Market Cap	1,113	8.9962	1.3464	9.5058	6.8688	10.3416
P/E Ratio	1,113	2.0795	0.7806	1.9260	1.2940	3.3228
Beta	1,113	1.2176	0.2633	1.2649	0.8320	1.4759

Note: This table presents summary statistics of dependent and independent variables used in the main empirical analysis specified in equation (1). For each series, mean, standard deviation, median, 10^{th} percentile and 90^{th} percentile values are demonstrated.

Table 3: Baseline Estimations

	(1) Close Close	(2) Close Close	(3) Parkinson	(4) Parkinson	(5) Garman Klass	(6) Garman Klass
NPL Ratio	0.683***	0.831***	0.589***	0.659***	0.744***	0.875***
	(0.171)	(0.170)	(0.137)	(0.123)	(0.184)	(0.167)
NPL Ratio x State	**4.292*****	**1.970*****	**4.048*****	**1.681*****	**5.445*****	**2.401*****
	(0.515)	**(0.525)**	**(0.367)**	**(0.354)**	**(0.497)**	**(0.486)**
Capital		-0.176		-0.055		-0.114
		(0.276)		(0.223)		(0.295)
Deposits		-0.062		-0.061		-0.076
		(0.074)		(0.052)		(0.071)
Securities		0.452***		0.481***		0.617***
		(0.060)		(0.047)		(0.064)
Bank Size		-0.032***		-0.021***		-0.031***
		(0.009)		(0.007)		(0.009)
Market Cap		0.015		0.000		0.007
		(0.012)		(0.009)		(0.013)
P/E Ratio		-0.036***		-0.021***		-0.032***
		(0.009)		(0.007)		(0.010)
Beta		0.194***		0.160***		0.218***
		(0.015)		(0.013)		(0.017)
Other Controls	No	Yes	No	Yes	No	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,113	1,106	1,113	1,106	1,113	1,106
Adjusted R-squared	0.213	0.409	0.330	0.541	0.310	0.524

Note: This table presents the estimation results of baseline regression model specified in equation (1). The sample covers observations of 7 publicly traded Turkish banks over the period 2008M5-2021M7. In columns (1) and (2), the dependent variable is stock price volatility measure $Close\ Close$ whereas columns (3)-(4) and columns (5)-(6) entail the dependent variables in the form of stock price volatility measures $Parkinson$ and $Garman\ Klass$, respectively. $State$ variable takes the value of one for state-owned entities in the sample, otherwise assuming the value of zero. $NPL\ Ratio$ is the main proxy for credit risk which is calculated as the ratio of non-performing loans total loans. In all columns, the main coefficient is attached to the interaction term $NPL\ Ratio\ x\ State$ which measures the degree of influence of bank ownership type on capital market discipline for credit risk. In all regressions, we control for bank and month fixed effects. In columns (2), (4) and (6), we include other bank-level control variables $Capital$, $Deposits$, $Securities$, $Bank\ Size$, $Market\ Cap$, $P/E\ Ratio$ and $Beta$. We winsorize all bank-level continuous variables at 1st and 99th percentiles. Detailed variable definitions are available in Table 1 and Appendix A. Robust standard errors are reported in parentheses. ***,** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 4: Robustness Analyses

Panel A: Entropy Balancing	(1) Close Close	(2) Parkinson	(3) Garman Klass
NPL Ratio x State	**1.099** (0.496)**	**1.193*** (0.389)**	**1.718*** (0.523)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	1,106	1,106	1,106
Adjusted R-squared	0.679	0.663	0.655

Panel B: Alternative Credit Risk Indicator	(1) Close Close	(2) Parkinson	(3) Garman Klass
Stage 2 Loan Ratio x State	**0.864*** (0.169)**	**0.903*** (0.142)**	**1.228*** (0.192)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	1,001	1,001	1,001
Adjusted R-squared	0.568	0.645	0.637

Panel C: Alternative Credit Risk Indicator	(1) Close Close	(2) Parkinson	(3) Garman Klass
Loan Loss Provisions Ratio x State	**4.229*** (1.304)**	**3.606*** (0.980)**	**4.352*** (1.310)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	1,106	1,106	1,106
Adjusted R-squared	0.405	0.537	0.519

Panel D: Two-Way Clustered Standard Errors	(1) Close Close	(2) Parkinson	(3) Garman Klass
NPL Ratio x State	**1.970*** (0.445)**	**1.681** (0.532)**	**2.401** (0.701)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	1,106	1,106	1,106
Adjusted R-squared	0.409	0.540	0.524

Panel E: Higher Degree Fixed Effects	(1) Close Close	(2) Parkinson	(3) Garman Klass
NPL Ratio x State	**2.009*** (0.546)**	**1.712*** (0.367)**	**2.446*** (0.504)**
Other Controls	Yes	Yes	Yes
Bank FE	No	No	No
Month FE	No	No	No
Observations	1,106	1,106	1,106
Adjusted R-squared	0.372	0.512	0.495

Panel F: Non-Winsorized Data	(1) Close Close	(2) Parkinson	(3) Garman Klass
NPL Ratio x State	**2.047*** (0.527)**	**1.719*** (0.362)**	**2.466*** (0.498)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes

	(1)	(2)	(3)
Month FE	Yes	Yes	Yes
Observations	1,106	1,106	1,106
Adjusted R-squared	0.403	0.527	0.509

Panel G: Alternative Lag Interval for Other Controls	(1) Close Close	(2) Parkinson	(3) Garman Klass
NPL Ratio x State	**2.139*** (0.527)**	**1.831*** (0.359)**	**2.609*** (0.493)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	1,092	1,092	1,092
Adjusted R-squared	0.399	0.525	0.509

Panel H: Quarterly Data Frequency (End-of-Quarter Balances)	(1) Close Close	(2) Parkinson	(3) Garman Klass
NPL Ratio x State	**1.875** (0.896)**	**1.672*** (0.610)**	**2.397*** (0.835)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	No	No	No
Observations	371	371	371
Adjusted R-squared	0.426	0.549	0.533

Panel I: Quarterly Data Frequency (Quarterly Average)	(1) Close Close	(2) Parkinson	(3) Garman Klass
NPL Ratio x State	**2.068** (0.906)**	**1.773*** (0.617)**	**2.537*** (0.846)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	No	No	No
Observations	371	371	371
Adjusted R-squared	0.392	0.523	0.506

Panel J: Controlling for Other Loan Portfolio Characteristics	(1) Close Close	(2) Parkinson	(3) Garman Klass
NPL Ratio x State	**1.643*** (0.499)**	**1.446*** (0.355)**	**2.065*** (0.481)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	1,106	1,106	1,106
Adjusted R-squared	0.414	0.543	0.527

Note: This table presents the estimation results of robustness checks utilizing the variants of the specification in equation (1). The sample covers observations of 7 publicly traded Turkish banks over the period 2008M5-2021M7. In all panels, columns (1), (2) and (3) entail the dependent variables $Close\ Close$, $Parkinson$ and $Garman\ Klass$, respectively. $State$ variable takes the value of one for state-owned entities in the sample, otherwise assuming the value of zero. $NPL\ Ratio$ is the main proxy for credit risk which is calculated as the ratio of non-performing loans total loans. Unless stated otherwise, in all panels, the main coefficient is attached to the interaction term $NPL\ Ratio\ x\ State$ which measures the degree of influence of bank ownership type on capital market discipline for credit risk. For the sake of brevity and space considerations, we only report the coefficients associated with the interaction terms. In panel (A), we implement entropy balancing procedure to re-weight the observations belonging to private banks in order to alleviate endogeneity concerns. In panel (B), we use original sample and consider the ratio of stage 2 loans to total loans ($Stage\ 2\ Loan\ Ratio$) in proxying credit risk. In panel (C), we use an alternative measure of credit risk in the form of the loan loss provisions normalized by total loans ($Loan\ Loss\ Provisions\ Ratio$). In panel (D), we follow two-way clustering strategy to compose standard errors based on bank and time dimensions. In panel (E), we drop individual bank and month fixed effects and saturate the model with bank-by-month higher degree fixed effects. In panel (F), we repeat the baseline regressions with the raw data without any winsorization. In panel (G), we prefer longer lag intervals for other control variables (3 months). In panel (H) and (I), we apply similar estimations to data with quarterly frequency. Lastly, in panel (J), we expand the set of control variables by accounting for the share of commercial loans and FX-denominated loans in total loans. Unless stated otherwise, in all regressions, we control for bank and month fixed effects. Unless stated otherwise, in all panels, we include other bank-level control variables $Capital$, $Deposits$, $Securities$, $Bank\ Size$, $Market\ Cap$, $P/E\ Ratio$ and $Beta$. Unless stated otherwise, we winsorize all bank-level continuous variables at 1st and 99th percentiles. Detailed variable definitions are available in Table 1 and Appendix A. Unless stated otherwise, robust standard errors are reported in parentheses. ***,** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 5: Credit Risk in Loan Breakdowns

Panel A: Housing Loans	(1) Close Close	(2) Parkinson	(3) Garman Klass
Housing NPL Ratio x State	**2.374*** (0.748)**	**1.682*** (0.492)**	**2.401*** (0.676)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	1,006	1,006	1,006
Adjusted R-squared	0.400	0.546	0.527
Panel B: Credit Cards	(1) Close Close	(2) Parkinson	(3) Garman Klass
Credit Cards NPL Ratio x State	**1.024*** (0.251)**	**0.449** (0.187)**	**0.732*** (0.252)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	1,106	1,106	1,106
Adjusted R-squared	0.476	0.590	0.574
Panel C: General Purpose Loans	(1) Close Close	(2) Parkinson	(3) Garman Klass
General Purpose NPL Ratio x State	**-2.171*** (0.453)**	**-2.005*** (0.350)**	**-2.558*** (0.475)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	1,106	1,106	1,106
Adjusted R-squared	0.392	0.529	0.510
Panel D: SME Loans	(1) Close Close	(2) Parkinson	(3) Garman Klass
SME NPL Ratio x State	**0.371** (0.176)**	**0.273** (0.127)**	**0.411** (0.175)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	1,106	1,106	1,106
Adjusted R-squared	0.399	0.540	0.521
Panel E: Micro Loans	(1) Close Close	(2) Parkinson	(3) Garman Klass
Micro NPL Ratio x State	**0.601*** (0.153)**	**0.583*** (0.116)**	**0.776*** (0.158)**
Other Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Observations	1,106	1,106	1,106
Adjusted R-squared	0.394	0.533	0.514

Note: This table presents the estimation results of baseline regression model specified in equation (1) adjusted to represent credit risk across different loan breakdowns. The sample covers observations of 7 publicly traded Turkish banks over the period 2008M5-2021M7. In all panels, columns (1), (2) and (3) entail the dependent variables $Close\ Close$, $Parkinson$ and $Garman\ Klass$, respectively. $State$ variable takes the value of one for state-owned entities in the sample, otherwise assuming the value of zero. $NPL\ Ratio$ is the main proxy for credit risk which is calculated as the ratio of non-performing loans total loans. In all panels, the main coefficient is attached to the interaction term $NPL\ Ratio\ x\ State$ which measures the degree of influence of bank ownership type on capital market discipline for credit risk. In panels (A), (B) and (C), we focus on sub-segments of consumer loans covering credit risk dynamics in housing loans, credit cards and general-purpose loans, respectively. In panels (D) and (E), we focus on sub-segments of commercial loans covering credit risk dynamics in SME and micro-firm loans. In all regressions, we control for bank and month fixed effects. For the sake of brevity and space considerations, we only report the coefficients associated with the interaction terms. In all panels, we include other bank-level control variables $Capital$, $Deposits$, $Securities$, $Bank\ Size$, $Market\ Cap$, $P/E\ Ratio$ and $Beta$. We winsorize all bank-level continuous variables at 1st and 99th percentiles. Detailed variable definitions are available in Table 1 and Appendix A. Robust standard errors are reported in parentheses. ***,** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 6: Estimations with Alternative Dependent Variables

	(1)	(2)	(3)	(4)
	Rogers Satchell	Yang Zhang	VaR	CVaR
NPL Ratio	0.628***	0.457***	0.017	0.042**
	(0.124)	(0.139)	(0.018)	(0.021)
NPL Ratio x State	**1.238*** **	**1.594*** **	**0.252*** **	**0.366*** **
	(0.330)	**(0.394)**	**(0.061)**	**(0.072)**
Other Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Observations	1,106	1,106	1,106	1,106
Adjusted R-squared	0.579	0.346	0.389	0.432

Note: This table presents the estimation results of baseline regression model specified in equation (1) extended with alternative stock price volatility measures as dependent variables. The sample covers observations of 7 publicly traded Turkish banks over the period 2008M5-2021M7. In columns (1) and (2), the dependent variables are $Rogers\ Satchell$ and $Yang\ Zhang$ while in columns (3) and (4), the dependent variables are VaR and $CVaR$, respectively. $State$ variable takes the value of one for state-owned entities in the sample, otherwise assuming the value of zero. In all columns, we include other bank-level control variables $Capital$, $Deposits$, $Securities$, $Bank\ Size$, $Market\ Cap$, $P/E\ Ratio$ and $Beta$. We winsorize all bank-level continuous variables at 1st and 99th percentiles. Detailed variable definitions are available in Table 1 and Appendix A. Robust standard errors are reported in parentheses. ***,** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table 7: Difference-in-Differences Analysis

	(1) Option-Implied Volatility	(2) Option-Implied Volatility
Post x State	**0.0248***** **(0.0065)**	**0.0455***** **(0.0102)**
Other Controls	No	Yes
Bank FE	Yes	Yes
Week FE	Yes	Yes
Observations	195	195
Adjusted R-squared	0.627	0.658

Note: This table presents the estimation results of DiD model specified in equation (2). The sample covers weekly observations of 5 publicly traded Turkish banks over the period 2019M10-2020M6. In both columns, the dependent variable, $Option - Implied\ Volatility$, is the implied volatility proxy derived from option contracts written on bank stocks based on deterministic volatility function approach. $State$ variable takes the value of one for state-owned entities in the sample, otherwise assuming the value of zero. $Post$ variable takes the value of one following the 2020M2 after the Covid-19 outbreak, otherwise assuming the value of zero. In both columns, the main coefficient is attached to the interaction term $Post\ x\ State$ which measures the degree of influence of bank ownership type on capital market discipline for credit risk. In both regressions, we control for bank and week fixed effects. In column (2), we include other high frequency bank-level control variables $Market\ Cap$, $P/E\ Ratio$ and $Beta$. Detailed variable definitions are available in Table 1 and Appendix A. Robust standard errors are reported in parentheses. ***,** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Appendix A

Baseline Volatility Measures

The initial method to calculate volatility, $Close\ Close$ takes closing prices of financial assets as an input for a given trading period to calculate the volatility in line with the following equation:

$$\sigma_{Close\ Close} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \bar{x})^2} \tag{1}$$

where x_i is the closing price of an asset, N is number of trading periods annualized by the number of periods within a year (Hull, 2003). We also benefit alternative volatility indicators considering the possible jumps within the trading window. As one method, Parkinson (1980) uses trading period highest and lowest values to calculate volatility as the following:

$$\sigma_{Parkinson} = \sqrt{\frac{1}{4Nln(2)}\sum_{i=1}^{N}\left(ln\left(\frac{h_i}{l_i}\right)\right)^2} \tag{2}$$

where h_i and l_i are highest and lowest prices for a given trading period, respectively. Continuous trading is one of the drawbacks of this approach as it does not consider closing price. However, Garman and Klass (1980) combines both intra-trading period and end of period prices to get more efficient volatility estimator in line with the following equivalence:

$$\sigma_{Garman\ Klass} = \sqrt{\frac{1}{2N}\sum_{i=1}^{N} ln\left(\frac{h_i}{l_i}\right)^2 - \frac{2\ln(2)-1}{N} ln\left(\frac{c_i}{o_i}\right)^2} \tag{3}$$

where c_i and o_i are closing and opening prices, respectively.

Beta Measure

In our empirical specification, the variable $Beta$ is utilized to account for the sensitivity to general market risk (Elyasiani and Zhang, 2015). As a systematic risk measure, bank-level $Beta$ indicator is calculated through the following auxiliary specification:

$$r_{it} = \alpha + Beta_{it} r_{mt} + v_{it} \tag{4}$$

where r_{it} is the return of bank stock i and r_{mt} stands for the return of market index (BIST-100 index). $Beta$ values being greater than 1 indicates that the stock return is more volatile than the corresponding market portfolio return. Moreover, this coefficient is widely employed to analyze the contribution of individual stock to overall portfolio risk, asset pricing, and cost of equity calculations.[11] As Blume (1975) has discussed equity betas have tendency to mean reversion to 1 and in line with generally accepted market practice, we further transform the indicator by using adjusted instead of raw versions of the $Beta$ which is defined as follows:

$$Beta_{adj,it} = 0.67 * Beta_{it} + 0.33 \tag{5}$$

Alternative Volatility Measures

$Parametric\ VaR$ is formulated as follows:

$$VaR_{\alpha} = \mu + \sigma\, Z(\alpha) \tag{6}$$

while $CVaR$ is expressed as the following:

$$CVaR_{\alpha} = E[\omega | \omega > Var_{\alpha}] \tag{7}$$

where μ represents asset return, σ stands for the volatility and $Z(\alpha)$ is the confidence level (which is taken as 5% in this exercise). After the calculations, we flip the signs of VaR and $CVaR$ measures by multiplying them with -1 to induce a similar interpretation with baseline stock price volatility series.

Option-Implied Volatility Measure

In line with the Deterministic Volatility Function (DVF) approach, volatility is structured as a deterministic function of strike price and time. This relation is outlined as the following:

---

[11] We calculate the bank-level *Beta* indicators with daily price data over 252-trading day moving windows and eventually aggregate them to the monthly frequency by taking end-of-month values (similar to the approach followed to synthesize stock price volatility indicators).

$$\sigma = max(0.01, a_0 + a_1X + a_2X^2 + a_3T + a_4T^2 + a_5XT) \tag{8}$$

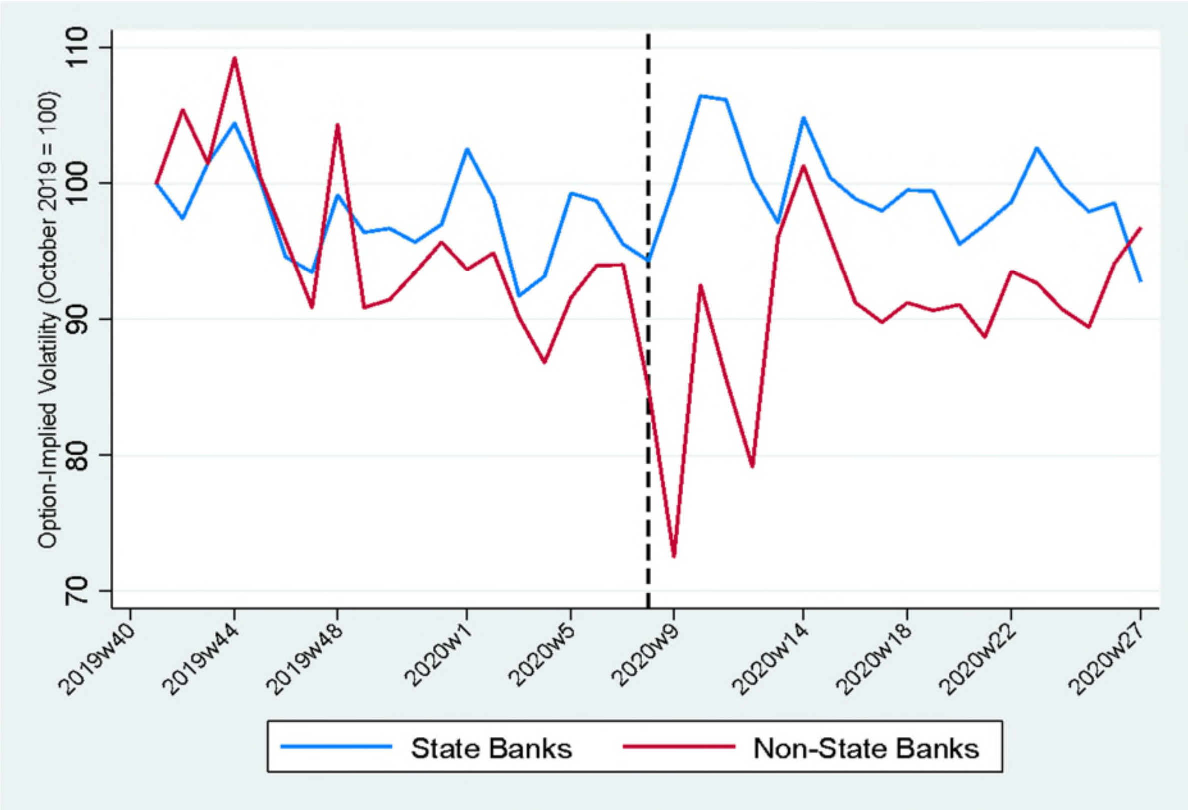
where X is exercise price of an option and T is time to maturity. Equation (8) uses maximum function to limit down volatility to 1%. For a given trading day, parameters $\Theta = [a_1, a_2, a_3, a_4, a_5]$ is estimated with non-linear least squares method as follows:

$$\min_{\Theta} SSE\ (\Theta) = \sum_{t=1}^{N} (\sigma_{BS} - \sigma_{DVF})^2 \tag{9}$$

where N is the number of contracts traded, σ_{BS} represents Black-Scholes implied volatility and σ_{DVF} symbolizes deterministic volatility. A particular concern with this technique is that the implied volatility for deep "in-the-money" options might have extreme values and distort the DVF fitting procedure. Dumas et al. (1998) proposes three exclusionary criteria to deal with distortion. Hence, decide to exclude options with maturities less than a week to have a sensible and precise volatility surface.

Appendix B

Figure B1: Parallel Trends Assumption



Note: This figure depicts the weekly course of the average option-implied volatility measures for state and non-state bank groups before and after the emergence of the Covid-19 outbreak. The series are normalized to 100 according to the beginning of the sample values for the identification of trends. The vertical dashed line represents the beginning of the post-treatment interval.

Table B1: Parallel Trends Test

	Treatment Group (N=57)	Control Group (N=38)	Test Statistic	p-value
Average Change in Option-Implied Volatility	-0.0013	-0.0019	0.1272	0.8990

Note: This table presents the estimation results of univariate parallel trends testing procedure. We begin with the sample period of the model specified in equation (2). In the second stage, we drop the post-treatment observations and calculate the momentum indicator for the dependent variable $Option - Implied\ Volatility$ throughout the pre-treatment phase. In the final step, we implement the simple t-test to compare this momentum indicator between state and private bank groups.

Table B2: Placebo Test 1

	(1) Option-Implied Volatility	(2) Option-Implied Volatility
Post x State	0.0053	0.0046
	(0.0041)	(0.0042)
Other Controls	No	Yes
Bank FE	Yes	Yes
Week FE	Yes	Yes
Observations	200	200
Adjusted R-squared	0.703	0.732

Note: This table presents the estimation results of placebo DiD model randomizing the treatment time. The sample covers weekly observations of 5 publicly traded Turkish banks over the year 2017 with similar duration of the sample period covered in Table 7. In both columns, the dependent variable, $Option - Implied\ Volatility$, is the implied volatility proxy derived from option contracts written on bank stocks based on deterministic volatility function approach. $State$ variable takes the value of one for state-owned entities in the sample, otherwise assuming the value of zero. In both columns, the main coefficient is attached to the interaction term $Post\ x\ State$ which measures the degree of influence of bank ownership type on capital market discipline for credit risk. In both regressions, we control for bank and week fixed effects. In column (2), we include other high frequency bank-level control variables $Market\ Cap$, $P/E\ Ratio$ and $Beta$. Detailed variable definitions are available in Table 1 and Appendix A. Robust standard errors are reported in parentheses. ***,** and * represent statistical significance at 1%, 5% and 10% levels, respectively.

Table B3: Placebo Test 2

Percentiles	Post x State Coefficient
1st	-0.0104
5th	-0.0075
10th	-0.0060
25th	-0.0031
50th	0.0000
75th	0.0032
90th	0.0058
95th	0.0075
99th	0.0108
Actual Coefficient	**0.0248**

Note: This table displays the percentile values of the empirical distribution of pseudo DiD coefficients obtained via placebo test 2 (randomizing treatment status). The last row represents the actual DiD coefficient retrieved from the empirical specification defined in column (1) of Table 7.

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