Belief Distortions and Lending Cyclicality: Evidence from Industry-Specialized Banks

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Abstract

This paper studies how industry specialization affects banks' belief formation and lending over the credit cycle. I show that when a specialized bank's preferred industry experiences a stock market runup, the bank expands lending and reduces loan loss provisions without tightening loan terms, despite the fact that industry performance declines from its runup-period peak in the years that follow. Loans originated under these conditions have a 62 basis point higher default rate than comparable loans made by nonspecialized banks to the same industry. Consistent with a diagnostic expectations framework, earnings call sentiment analysis reveals that specialized banks express heightened optimism toward their preferred industries during booms. The results highlight a downside of expertise in financial intermediation: specialization can amplify credit cycles by distorting beliefs.

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1 Introduction

A prevailing view in the banking literature asserts that specialized banks, those concentrating a large share of their lending in a single industry, enjoy an informational advantage when in their preferred sectors. The argument runs that repeated screening, monitoring, and lending to firms in the same industry builds industry-specific expertise that diversified competitors cannot easily replicate. Consistent with this argument, prior work documents that specialized lenders extend credit at lower spreads, with looser nonprice terms, and with lower rates of nonperformance on average within their core industries (Blickle et al., 2026, 2025; Giometti et al., 2025). Under this view, specialization is thought to act as a buffer against credit risk by sharpening screening and improving the allocation of credit.

This paper documents a departure from this view, one that emerges once we look at how specialized banks behave over the credit cycle. Using a panel of syndicated loans from 1996 to 2019, I show that when a specialized bank's preferred industry experiences a stock market runup, the bank acts contrary to the behavior expected of a lender with superior information. It expands lending and reduces its loan loss provisions, even though industry performance, on average, declines from its runup period peak in the years that follow. Specialized banks do not tighten loan terms in response: they do not raise spreads, demand more collateral, or shrink loan sizes. The loans they originate in their preferred industry in the year following such a runup experience a 62 basis point higher default rate than comparable loans made by nonspecialized banks to the same industry at the same time. This 62 basis point differential is both statistically and economically meaningful, corresponding to 12.6 percent of the sample mean default rate. The cross-sectional informational advantage that specialized banks generally enjoy thus appears to break down and inverts around episodes of strong industry-level returns.

To explain this puzzle, I propose that the heterogeneous response to industry runups reflects a difference in how specialized and diversified banks update their beliefs, rather than a difference in their underlying screening technology. I formalize this in a model based on the diagnostic expectations framework of Bordalo et al. (2020). A specialized bank concentrates on a single industry and observes a more precise signal about its fundamentals; a diversified bank spreads its attention across sectors and observes a noisier signal about any one of them. Both banks share the same degree of diagnostic overreaction. The asymmetry comes from signal precision: because the specialized bank trusts its sharper signal, it places more weight on incoming news, and the shared diagnostic distortion, applied to this larger updating gain, produces more extreme beliefs. During a runup the specialized bank therefore overreacts more, becomes more optimistic about its industry, and lends on looser terms than its diversified peer. The model delivers a number of empirical implications; I focus on two that I take to the data: specialized banks should hold systematically more optimistic beliefs about their preferred industry during runups, and the differential should be larger in opaque industries, where the specialized bank's informational advantage is greatest.

Two direct tests of the mechanism support this interpretation. First, using a large language model to score executive sentiment in bank earnings calls, I find that specialized banks express significantly more positive sentiment toward their preferred industries during the runup window than nonspecialized banks discussing the same industries, and the differential reverses once the runup ends. The optimism is not a permanent feature of specialized banks' communications; it is concentrated in the runup window. Second, the differential default risk associated with specialized banks during runups is substantially larger in industries with sparse credit rating coverage, a proxy for industries in which fundamentals are noisier and harder to evaluate. Both tests align with the model's predictions.

A series of alternative explanations cannot fully account for the patterns. Industry capture, the idea that specialized banks extract rents from captive borrowers, does not explain the results: adding capture and its interactions leaves the specialization-runup interaction positive and statistically significant. Geographic clustering and prior lending relationships, both of which could in principle generate borrower specific knowledge that travels with industry concentration, similarly fail fully subsume the documented effect. Most directly, the elevated default risk is concentrated entirely among loans that specialized banks make to their preferred industry: the same banks' lending outside that industry, including during runups, looks no different from that of nonspecialized banks. The mechanism is industry specific, consistent with industry specific belief formation rather than a general appetite for risk.

This paper makes three main contributions. First, it documents a state contingent reversal of the informational advantage associated with bank specialization: a buffer against credit risk on average, specialization becomes an amplifier of risk during industry runups. Second, it provides micro-level evidence that bank-level belief distortions can help drive credit cycles, and that organizational structure, and specifically portfolio specialization, shapes the magnitude of those distortions. Third, by tracing the heterogeneous response to runups to differences in information sets rather than differences in the underlying bias, it offers a tractable mechanism through which heterogeneous information across financial intermediaries can generate systematic differences in lending behavior.[1]

The remainder of the paper proceeds as follows. Section 2 reviews the related literatures on

[1]For related work on belief distortions and credit cycles, see Bordalo et al. (2019); Ma et al. (2020); Barrero (2022); Gulen et al. (2024).

credit cycles, belief distortions, and bank specialization. Section 3 describes the data and the construction of key variables. Section 4 presents the central empirical puzzle: specialized banks expand lending, lower provisions, and originate higher defaulting loans during industry runups, even though industry performance, on average, declines from its runup period peak thereafter. Section 5 introduces a diagnostic-expectations model that rationalizes the puzzle and generates testable predictions. Section 6 provides two direct tests of the mechanism using earnings-call sentiment and cross-industry heterogeneity in opacity. Section 7 considers and rules out alternative explanations. Section 8 reports robustness checks. Section 9 concludes.

2 Literature Review

Credit booms are systematically followed by sharp increases in defaults and financial distress, raising the central question of why banks relax lending standards during expansions. A large literature studies the drivers of such credit cycles. One strand emphasizes optimism and mispricing: banks with rapid loan growth tend to be overly optimistic about borrower quality and subsequently experience elevated crash risk (Fahlenbrach et al., 2018), while fluctuations in investor sentiment and risk appetite play a central role in credit market expansions (López-Salido et al., 2017; Baron and Xiong, 2017). Other explanations focus on institutional frictions, including short-term managerial incentives (Rajan, 1994), weakened screening when loan demand surges (Dell'ariccia and Marquez, 2006; Ruckes, 2004), and the erosion of institutional memory following prolonged periods of stability (Berger and Udell, 2004). Together, this literature shows that lending standards deteriorate during booms, but the underlying mechanism, whether distorted beliefs, competitive pressure, or incentive problems, remains debated.

A related and growing body of work highlights distorted beliefs as a key driver of credit expansions. Periods of high issuance are associated with declining borrower quality and subsequent low returns, consistent with systematic underpricing of risk (Greenwood and Hanson, 2013). Behavioral mechanisms further amplify these dynamics: investors and financial intermediaries extrapolate from recent low default rates, leading to overly optimistic assessments of credit risk (Greenwood et al., 2023; Bordalo et al., 2018). While this literature documents aggregate patterns consistent with misperceptions, less is known about how such distortions arise within financial intermediaries or why some banks may be more prone to them than others. I contribute to this literature by showing that belief distortions are not uniform across banks: specialization systematically amplifies optimism during industry runups, leading to excessive credit expansion and subsequent deterioration in loan performance.

This paper also contributes to the literature on bank specialization. A common view is that specialization enhances information production and screening. Consistent with this perspective, specialized banks may support their core industries during downturns and, on average, exhibit lower rates of nonperformance (Blickle et al., 2026). Related evidence points the same way: in Brazilian banking, loan portfolio concentration raises returns and lowers default risk (Tabak et al., 2011), and diversification across sectors does not reliably improve returns or safety (Acharya et al., 2006). More recently, a growing literature documents real effects of specialization on credit allocation and borrower outcomes, particularly in response to shocks (Giannetti and Saidi, 2019; Iyer et al., 2022; Saidi and Streitz, 2021; Paravisini et al., 2023).

I build on this literature by shifting the focus from outcomes to belief formation. While specialization may improve information on average, concentrated exposure can also distort inference when recent industry performance is unusually strong. During runups, specialized banks receive disproportionately strong signals from their preferred industries, which can lead to systematic overextrapolation. I show that this mechanism results in a temporary loosening of lending standards and a subsequent increase in defaults, linking organizational structure directly to belief distortions during credit booms.

Among existing work, my paper is most closely related to Blickle et al. (2026), though the two papers differ fundamentally in their empirical focus. Whereas they study specialized bank performance unconditionally, examining how specialization shapes loan outcomes on average across all economic environments, my analysis is explicitly conditional, asking how specialization interacts with industry runups to shape belief formation and lending behavior over the credit cycle. This distinction matters because the unconditional relationship between specialization and loan performance may mask meaningful heterogeneity: a specialized bank may perform well on average because runup periods are relatively rare in any given sample. Consistent with this, Blickle et al. (2026) analyze loans issued over the relatively narrow window of 2011–2020, whereas my analysis spans 1996–2019 and is designed around identifying runup episodes explicitly. Over two-thirds of the runups in my sample occur prior to 2011, suggesting that the 2011–2020 window captures relatively few of the episodes that drive my main results.

Beyond sample scope, the two papers also differ in how loan performance is measured. Whereas Blickle et al. (2026) capture whether a bank internally downgrades a borrower's credit quality, my analysis considers whether the borrower ultimately defaults, a more consequential and permanent indicator of repayment failure that is observable without access to confidential supervisory data. Despite these differences, I am able to reproduce several of their core cross-sectional patterns in unreported tables:[2] specialized banks concentrate lending in their preferred industries, extend credit

[2] My replication of Blickle et al. (2026) is necessarily partial. Their analysis relies on the FR Y-14Q supervisory

at lower spreads, and lend more readily to opaque borrowers, proxied by smaller firm size. While Blickle et al. (2026) document that specialized banks are less likely to issue loans to borrowers that receive an internal credit downgrade, I obtain qualitatively similar results using publicly observable credit rating downgrades, suggesting that the cross-sectional patterns are robust to data source, and that the divergence in our findings on loan performance reflects the conditional nature of my analysis rather than a fundamental disagreement about how specialization affects the performance of banks.

3 Data

This section describes the construction of the loan-level sample, the measurement of bank specialization, and the definition of industry stock market runups. The empirical design combines syndicated loan data with bank balance sheet information and industry-level equity returns to examine how bank lending behavior varies with specialization following industry runups.

3.1 Data Sources and Sample Construction

Key data for this paper come from three main sources. Balance sheet and accounting metrics are sourced from Standard and Poor's Compustat, industry stock return data comes from CRSP, and syndicate loan-level data is obtained from Thomson Reuters' LPC DealScan.[3] Despite its focus on relatively large loans and firms, DealScan represents one of the primary detailed loan-level

data, a confidential regulatory dataset tracking all C&I loans exceeding $1 million for stress-tested U.S. banks, which is available only to Federal Reserve researchers. In its place, I use LPC DealScan, which covers the syndicated loan market but does not provide full portfolio-level loan data for all banks.

[3]WRDS has updated the DealScan dataset starting from the summer of 2021. The update consisted of a reorganization of the entire dataset, combining all the information into a single table and changing loan identifiers. Due to complications with linking the current version of DealScan to Compustat, the discussion here is based on an older vintage, which was organized around several different tables, and is now considered the "legacy" version on WRDS.

sources of information on US firms' credit relationships, spanning 40 years (from 1984 to today). It is commonly used to study bank lending (Bharath et al., 2011) and its implications for the real economy (Chakraborty et al., 2018; Chodorow-Reich, 2014). Although DealScan coverage begins in the early 1980s, reporting improves substantially during the 1990s (Chava and Roberts, 2008). I collect syndicated loan originations beginning in 1991. Because specialization is computed using a five year lookback window, the baseline analysis begins in 1996 and extends through 2019.[4]

DealScan collects information on two different levels: loan packages, or deals, and loan facilities. A given package generally includes one or more loan facilities. For my analysis, I limit the sample to all the loan facilities whose borrowers can be matched to Compustat using the linking table provided by Chava and Roberts (2008) and whose lenders can be matched to Compustat Bank using the linking table provided by Schwert (2018). Most loans in DealScan are syndicated and involve one or more lead arrangers and participant lenders. Because lead arrangers retain primary screening and monitoring responsibilities, I attribute each loan exclusively to its lead arranger(s), following Chakraborty et al. (2018). This restriction governs which lenders are linked to a facility, not the dollar amount assigned to each: a facility with multiple lead arrangers generates one bank–borrower–facility observation per lead, and each lead is assigned its own estimated exposure rather than the full facility amount. The construction of that exposure is described in Section 3.2. In the case of mergers among lenders, loans are attributed to the surviving holding company from the merger year onward. I restrict the sample to U.S.-syndicated loans denominated in U.S. dollars and to borrowers incorporated in the United States. Borrowers in financials (SIC 6000–6999), utilities (SIC 4910–4939), and miscellaneous industries (SIC 9900–9999) are excluded. Unless

[4]The linking table provided by Schwert (2018) currently ends in 2019, which determines the endpoint of the sample period.

otherwise noted, the unit of observation is the bank–borrower–facility level. The exception is the default analysis of Section 4.3, which is conducted at the bank–borrower–facility–year level so that default status can be measured in each year a loan is outstanding. To ensure that specialization is measured reliably, and not dominated by a few infrequent lenders, I require that a bank originate at least five syndicated loans in the preceding five years. All continuous variables are winsorized at the 1st and 99th percentiles unless naturally bounded.

To examine bank-level balance sheet responses, I obtain Call Report data from FR-Y9C filings via the Federal Reserve's National Information Center. Earnings conference call transcripts used in sentiment analysis are sourced from Capital IQ. Dollar-denominated variables are deflated to constant 2019 dollars using the Consumer Price Index for All Urban Consumers when stated; unless otherwise noted, regressions are conducted in nominal terms.

3.2 Loan Ownership Approximation

DealScan loan origination data, while widely used, is subject to several well documented limitations. First, lender share information at origination is reported for only a small subset of loans, and the reporting is non-random (Bharath et al., 2011; Schwert, 2018; Giannetti and Saidi, 2019; Blickle et al., 2020). Second, lenders often sell loan holdings shortly after origination (Blickle et al., 2020). As a result, the composition of loan ownership in the days following origination may diverge significantly from the initial syndicate structure. To mitigate these challenges, I approximate post-origination bank exposures following Blickle et al. (2020), who combine DealScan with the Shared National Credit (SNC) Registry. When lender shares are reported in DealScan, I scale them using holding coefficients estimated from regressions of realized SNC exposures on

DealScan shares provided by Blickle et al. (2020). When shares are not reported, I impute post-origination exposures using a regression model estimated in SNC data that predicts loan holdings based on observable DealScan characteristics. This procedure yields a consistent approximation of bank-level loan exposures across the sample. The resulting estimated exposure is the loan amount used throughout the paper. Wherever a bank-specific loan amount appears, including $\text{LoanAmt}_{b,i,\tau}$ in the specialization measure defined below, the industry-capture measure of Section 7.1, and the *Ln(Amount)* variable used as a loan control and as a dependent variable in Section 4.4, it refers to this estimated post-origination exposure rather than to the full facility amount or to the raw DealScan share.

3.3 Bank Specialization

Bank specialization is measured in a similar fashion to Blickle et al. (2026). While Blickle et al. (2026) compute specialization as the contemporaneous share of a bank's portfolio using supervisory loan holdings data, DealScan records originations rather than holdings. I therefore compute specialization over a five-year lookback window of loans originated in the preceding five years, which approximates a bank's current portfolio given typical loan maturities. This approach is consistent with how relationship lending is measured in the DealScan literature more broadly (e.g., Bharath et al. 2011; Giometti et al. 2025). For each bank b in year t, I compute the share of its syndicated lending concentrated in each 2-digit SIC industry over the preceding five years, where $\text{LoanAmt}_{b,i,\tau}$ denotes bank b's estimated retained exposure to loans it lead-arranged to industry i in year τ, constructed as described in Section 3.2 above:

$$\text{Specialization}_{b,t} = \max_i \left(\frac{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{b,i,\tau}}{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{b,\tau}} \right). \tag{1}$$

This measure captures the degree to which a bank's recent lending activity is concentrated in a single industry. By construction, specialization is based exclusively on lagged lending and is therefore predetermined relative to contemporaneous lending and future industry performance.

Because the relationship between portfolio concentration and lending behavior is unlikely to be linear, I construct a binary indicator, *Specialized Bank*. The threshold is set at the top quartile of the pooled bank-year distribution of $\text{Specialization}_{b,t}$, which in my sample falls at a concentration share of 20%. The operative rule applied throughout the paper is therefore $\text{Specialization}_{b,t} \geq 0.20$: the indicator equals one when a bank's five-year concentration in a single industry is at least 20%, and zero otherwise.

Using a percentile-based threshold has two advantages. First, it allows for flexible nonlinear effects without imposing a functional form. Second, it defines specialization relative to the cross-sectional distribution of bank portfolios rather than an arbitrary concentration level. The top-quartile cutoff identifies banks whose lending is substantially more concentrated than the typical bank while retaining sufficient cross-sectional variation for estimation. Results are robust to using the continuous specialization measure, or other cutoff values for specialization.

Specialization is persistent over time. Conditional on being classified as specialized in a given year, a bank remains specialized in the following year with probability 74% (conditional on survival), indicating that specialization reflects relatively stable lending focus rather than short-term portfolio fluctuations.

3.4 Industry Stock Market Runups

Industries are defined using 2-digit SIC codes. Monthly stock returns are computed from CRSP using common shares (share codes 10 and 11). Firms are assigned to industries based on the most recent available SIC code. To identify periods of unusually strong industry performance, I construct three-year cumulative industry returns in excess of the market using equal-weighted firm returns. Formally, $Runup_{i,t} = 1$ if the cumulative excess return in industry i over years $t-3$ through $t-1$ is at least 20%, and zero otherwise.

The timing convention should be made explicit, since the same word can refer either to the returns or to the year the indicator marks. I refer to the three years $t-3$ through $t-1$, over which the excess return accumulates, as the runup years; these correspond to event time $k \in \{-3, -2, -1\}$ in the event studies of Section 4. The year t that $Runup_{i,t}$ marks is the first of the years subsequent to the runup, event time $k = 0$. A loan with $Runup_{i,\tau(l)} = 1$ is therefore originated in the first post-runup year, after the three-year appreciation has already occurred rather than during it.

This convention is deliberate rather than incidental. Because the entire return window closes before the indicator year begins, the returns that define a runup are predetermined at the moment a loan is originated. There is no mechanical overlap between the price movement being measured and the credit decision being studied, and no scope for the loan itself to enter the return that classifies it. The interpretation throughout is thus that banks lend on the strength of an appreciation that has already been realized and is publicly observable, which is precisely the setting in which extrapolative or diagnostic beliefs would be expected to operate.

I use runup episode as an umbrella term for the runup years and the years subsequent to the runup taken together, and phrases such as "around a runup" refer to this span. Where a specific estimate is reported, I identify the window it comes from: the bank-level event studies of Section 4.2 are read off particular event years, while the loan-level results of Sections 4.3 onward concern loans originated in the first post-runup year.

The 20% return cutoff ensures that runups capture the upper tail of sustained industry performance rather than transitory price movements. The three-year horizon focuses on prolonged expansions that are economically meaningful for credit supply decisions, consistent with the idea that banks respond to persistent shifts in industry conditions rather than short-lived fluctuations. To ensure that runups reflect genuine expansions rather than a scenario where the market languished, but the industry experienced a flat performance, I additionally require the corresponding three-year raw industry return to be positive. Following Greenwood et al. (2019), I impose a five-year exclusion window within each industry to avoid overlapping runup episodes. Approximately 11% of loan originations occur during industry runups. Figure 2 visualizes the resulting classification across industries and years, with the outlined cells marking the industry-years identified as runups.

3.5 Descriptive Statistics

The final sample includes 110 bank holding companies matched to 2,119 unique borrowing firms. Applying the top-quartile cutoff to the pooled bank-year distribution classifies 204 of the 820 bank-year observations, or approximately 25%, as specialized; Table A.2 reports the annual breakdown. Specialized banks originate approximately 24% of loans in the sample, close to their bank-year share. Of the loans they do originate, roughly three-fifths are extended to their preferred industry. I identify 54 distinct industry runups over the sample period. Runups cluster in the late 1990s, mid-2000s, and early-to-mid 2010s. Only a small number of industries experience more than one runup. Importantly, this method captures several sectors that are widely recognized as having experienced notable booms such as electronic equipment and technology firms during the late 1990s, and energy related commodities and building materials in the years leading up to the 2007 peak.

Summary statistics are reported in Table 1. There appear to be several systematic differences between specialized and nonspecialized banks. Small banks are much more likely to be specialized (the correlation between bank size and specialization status is -0.22). Additionally, specialized banks are more likely to lend to smaller, younger, less profitable firms.

4 Specialized Banks Around Industry Runups

This section establishes the empirical patterns that motivate the rest of the paper. I first show that industry stock market runups are not permanent improvements in fundamentals: profitability, equity returns, and debt growth all decline from their runup-period peaks in the years that follow, reverting toward the mean. I then document that, despite this subsequent reversion, specialized banks expand their overall commercial lending and reduce their loan loss provisions during the runup years in which their preferred industry's stock price is appreciating. At the loan level, the loans they originate in the first post-runup year default at substantially higher rates than comparable loans made by nonspecialized banks to the same industry, without any compensating tightening of contract terms at origination. Together, these patterns are difficult to reconcile with the conventional view that specialization confers an informational advantage that should sharpen credit allocation precisely in the industries the bank knows best.

4.1 Industry Runups and Industry Reversals

A natural first question is whether the runups I study correspond to durable improvements in industry fundamentals or whether industry performance subsequently declines from its runup-period peak. To address this, I estimate a stacked difference-in-differences event-study at the industry level. For each runup episode, I construct a sub-dataset consisting of the treated industry and a set of clean control industries, those with no runup activity anywhere within the estimation window, and stack these sub-datasets to form the estimation sample. This stacking approach guards against contamination bias that arises when control units are themselves approaching or recovering from runup episodes (Cengiz et al., 2019).

The omitted reference period is $t-4$, the year before the runup begins, against which all other event-time coefficients are interpreted. The specification is:

$$
\begin{aligned}
y_{i,t,s} = \sum_{k \neq -4} \beta_k \big(\mathbf{1}[k_{i,t,s} = k] \times \mathit{Treated}_{i,s}\big) \\
+ \gamma_{i,s} + \lambda_{t,s} + \varepsilon_{i,t,s}, \qquad (2)
\end{aligned}
$$

where s indexes the stack (runup episode), $k \in \{-5, -3, -2, -1, 0, +1, +2\}$ denotes event time relative to the first post-runup year ($k = 0$), with $k = -4$ omitted as the reference period, and $\mathit{Treated}_{i,s}$ is an indicator equal to one for the treated industry in stack s. $y_{i,t,s}$ denotes one of three industry-level outcomes: (i) return on assets (ROA), (ii) raw equal-weighted stock return, (iii) year-over-year log growth in total industry debt.[5] $\gamma_{i,s}$ and $\lambda_{t,s}$ denote stack-by-industry and stack-

[5]Following Greenwood et al. (2010), total industry debt is defined as the sum of short-term and long-term debt.

by-year fixed effects, respectively, which absorb any time-invariant differences across industries within a stack and any aggregate shocks common to all industries in a given stack-year. Standard errors are clustered at the industry level.

The pre-runup lead $k = -5$ serves as a placebo test: absent pre-existing trends, the coefficient at $k = -5$ should be statistically indistinguishable from zero. The runup years $k \in \{-3, -2, -1\}$ capture dynamics during the appreciation itself, while $k \in \{0, +1, +2\}$ trace outcomes in the years subsequent to the runup.

The coefficients β_k trace the evolution of industry outcomes before, during, and after runup episodes. The full specification is reported in Table A.4 and the estimates are plotted in Figures 3, 4, and 5. During the runup years, all three outcomes are elevated relative to the pre-runup baseline at $k = -4$. Industry ROA rises steadily to 3.31 percentage points above baseline by $k = -1$, equal-weighted excess returns run close to three percentage points above baseline throughout $k \in \{-3, -2, -1\}$, and log debt growth is 11 to 13 log points higher, with the return and debt-growth coefficients significant at the one percent level in every runup year.

Once the runup period ends, industry performance declines on all three margins. Equal-weighted excess returns fall from roughly three percentage points above the pre-runup baseline during the runup years to essentially zero from $k = 0$ onward, and log debt growth falls from 11 to 13 log points above baseline to values statistically indistinguishable from it. Industry ROA declines from its $k = -1$ peak of 3.31 percentage points to between 1.06 and 2.73 percentage points in the years that follow. The pattern is one of reversion to the mean: the exceptional performance that defines a runup is not sustained, and industries give back most or all of their outperformance within three years.

The decline is measured from the runup-period peak rather than from the pre-runup baseline, and this distinction matters for what the estimates can be said to establish. Because $k = -4$ is the omitted category, every coefficient in Table A.4 is expressed relative to an ordinary year rather than to the runup itself. Read against that baseline, returns and debt growth revert to their pre-runup norms and industry ROA remains modestly elevated at $k = +1$ and $k = +2$; no outcome falls significantly below its pre-runup level at any post-runup horizon. The evidence therefore establishes that runup-period outperformance is transitory, not that industries end up worse off than they began.

For each of the three outcomes, every post-runup coefficient lies below the maximum attained during the runup years $k \in \{-3, -2, -1\}$. This pattern of strong performance during an expansion followed by reversion toward normal conditions is consistent with well-documented cyclical dynamics in credit markets both at the aggregate level (Bernanke and Gertler, 1989; Kiyotaki and Moore, 1997; Berger and Udell, 2004; Becker and Ivashina, 2014; Bordalo et al., 2026) and at the industry level (Fahlenbrach et al., 2018).

These patterns indicate that runups do not mark permanent shifts to a higher performance path: the outperformance observed during the runup years fades in the years that follow. This mean reversion is what matters for the interpretation of the bank-level results below. A lender that extends credit on the expectation that runup-period conditions will continue is disappointed, even though the industry does not end up worse than it was beforehand. That is precisely the form of disappointment a diagnostic-expectations mechanism predicts, since overreaction generates forecasts that are subsequently revised toward the mean rather than industries that collapse outright.

4.2 Specialized Bank Lending and Provisioning Around Runups

I now examine how the lending and provisioning behavior of specialized banks evolves around industry runups. To address concerns about treatment effect heterogeneity across runup cohorts, I adopt a stacked difference-in-differences design that compares specialized banks whose preferred industry experiences a runup to otherwise similar banks that are unexposed to any runup over the same window.

For each treated episode, a year in which a specialized bank experiences a runup in its primary industry, I construct a cohort pairing the treated bank with control banks that exhibit no runup activity anywhere within the event window. I then stack these cohorts and estimate the following event-study regression on the pooled dataset.

Formally, for bank b in year t within cohort s I estimate

$$\begin{aligned} y_{b,t,s} = &\sum_{k\neq -4} \delta_k \big(\mathbf{1}[k_{b,t,s} = k] \times \text{TreatedUnit}_{b,s}\big) \\ &+ \phi_{b,s} + \lambda_{t,s} + \varepsilon_{b,t,s}, \end{aligned} \tag{3}$$

where $k \in \{-5, -3, -2, -1, 0, +1, +2\}$ indexes event time relative to the first post-runup year ($k = 0$), and $y_{b,t,s}$ is the outcome of interest. It is either the $\text{LoanRatio}_{b,t}$, which is C&I lending over total assets, or loan loss provisions, defined as total loan loss provisions divided by total assets, multiplied by 100. $\text{TreatedUnit}_{b,s}$ is a binary indicator equal to one if bank b is the specialized bank assigned to cohort s. The omitted reference period is $k = -4$, the year before the runup begins. $\phi_{b,s}$ and $\lambda_{t,s}$ denote cohort $\times$ bank and cohort $\times$ year fixed effects, respectively, which absorb time-invariant bank heterogeneity and aggregate time shocks within each cohort. Control banks are restricted to institutions with no runup activity during the $[-5, +2]$ window, ensuring a clean counterfactual. Standard errors are clustered at the bank level.

A few important implementation details and identification remarks are worth emphasizing. First, the preferred industry for each bank is defined using the lagged (pre-event) specialization measure so that event timing is not mechanically driven by contemporaneous portfolio reallocation. For both specialized and nonspecialized banks, the preferred industry is defined as the industry with the highest lending share over the preceding five years, consistent with Equation (1). The Specialized Bank$_{b,t}$ indicator then captures whether that concentration exceeds the top quartile of the sample distribution. Treatment in a cohort is therefore assigned to a bank that is specialized and whose preferred industry runs up; every other bank in that cohort is unexposed by construction, since control eligibility requires the absence of any runup in the bank's preferred industry throughout the $[-5, +2]$ window. Second, because specialization is calculated from lagged lending (the five-year lookback), the Specialized Bank$_{b,t}$ indicator is predetermined with respect to runups and contemporaneous loan originations. Third, the coefficients δ_k are interpreted as the change in the loan ratio of specialized banks experiencing a runup in their preferred industry, in event year k relative to $k = -4$, measured against contemporaneous control banks with no runup exposure and controlling for bank fixed effects and common time shocks. They are an average treatment effect on the treated rather than a specialized-versus-nonspecialized contrast at a common runup: the treatment bundles specialization with runup exposure, and the differential response of specialized and nonspecialized lenders to the same industry runup is identified instead at the loan level in Section 4.3, where industry-by-origination-year fixed effects hold the runup episode fixed.

The screen used to determine control eligibility warrants additional discussion. Runup exposure is evaluated at each bank's preferred industry, the industry with the highest lending share over the preceding five years, symmetrically for treated and control banks. This yields a one-to-one match between banks and runup episodes, so that each bank contributes at most one runup observation per year, and it applies the same exposure definition on both sides of the comparison.

The cost of this approach is that, for less concentrated banks, the distinction between the top industry and the second- or third-ranked industry may be economically small. A bank with lending shares of 18%, 17%, and 15% across its top three industries is screened only on the first, even though its exposure to the other two is nearly identical. A control bank whose second-ranked industry runs up therefore remains in the cohort despite holding meaningful exposure to a runup industry.

A stricter alternative would exclude from the control pool any bank in which any industry with positive exposure experiences a runup during the window. This would sharpen the counterfactual, but at a substantial cost: it disproportionately screens out diversified institutions, since a bank lending across many industries is mechanically more likely to touch some runup somewhere in an eight-year window, leaving a control pool skewed toward small and narrowly exposed banks that are poor comparisons for the treated group. The preferred-industry screen retains a broader and more comparable set of controls. Because any residual runup exposure among controls moves them in the same direction as the treated banks, it attenuates the estimated δ_k and works against finding an effect.

Figure 6 reports the δ_k estimates for $\text{LoanRatio}_{b,t}$ while Table A.5 reports the full specification. Relative to the pre-runup baseline at $k = -4$, and relative to control banks unexposed to any runup, specialized banks increase their C&I exposure during the runup years $k \in \{-3, -2, -1\}$ and revert toward the baseline in the years subsequent to the runup ($k \geq 0$). This is striking given the evidence in Section 4.1 that industry performance declines from its runup-period peak: specialized banks lend most aggressively when their industry of specialization is likely to revert.

To assess whether this increase in lending is accompanied by stricter provisioning due to greater forward-looking risk recognition, I reestimate Equation (3) replacing the dependent variable with loan loss provisions (LLP), defined as total loan loss provisions divided by total assets, multiplied by 100. Figure 7 reports these δ_k estimates. Relative to the pre-runup baseline at $k = -4$, and relative to unexposed control banks, specialized banks reduce provisions during the runup years $k \in \{-3, -2, -1\}$ and revert toward the baseline only in the years subsequent to the runup ($k \geq 0$); they do not raise provisions contemporaneously with the runup. Combining the two outcomes, specialized banks behave as though a runup in their industry of specialization represents good news for credit risk, expanding commercial exposure and reducing provisioning when the industry-level evidence in Section 4.1 indicates that performance is about to revert.

4.3 Loan-Level Default Risk

The bank-level evidence shows that specialized banks expand exposure and reduce provisioning over the runup years. A natural follow-up question is whether the loans they originate in the first post-runup year also perform worse ex post, holding constant industry-time conditions and observable borrower characteristics. I now estimate a linear probability model of loan default at the loan level. For this and all subsequent loan analysis, the specialized bank loan sample is restricted to loans issued by specialized banks to borrowers in their preferred industry. Loans made by specialized banks outside their primary industry are excluded in order to focus on lending decisions made within the bank's area of specialization.

The analysis is conducted at the loan-year level, so that the sample resembles a pseudo credit registry: each facility contributes one observation for every calendar year in which it is outstanding. Following Murfin (2012), *Default*$_{blfi,t}$ is an indicator equal to one if borrower f's S&P credit rating is "Default" or "Selective Default" in year t and loan l is still active in that year, and zero otherwise. The variable therefore records default status in each year of exposure rather than a single time-invariant outcome assigned to the facility: a borrower that remains in default or selective default for several years while the loan is outstanding contributes a one in each of those years. This panel structure expands the 21,790 bank–borrower–facility originations that remain after the focal-industry restriction described above into roughly 84,000 loan-year observations. I follow the adjustment procedure in Blickle et al. (2020) to account for loans originated for near-term distribution, ensuring that the default measure reflects credit risk retained at origination rather than the effect of loans issued for the purpose of distribution.

For bank b issuing loan l to firm f in industry i, originated in year $\tau(l)$ and observed in calendar year t, I estimate:

$$\begin{aligned}\text{Default}_{blfi,t} = {} & \beta_1 \text{Specialized Bank}_{blfi} + \beta_2 \text{Runup}_{i,\tau(l)} \\ & + \beta_3 \big(\text{Specialized Bank}_{blfi} \times \text{Runup}_{i,\tau(l)}\big) \\ & + \mathbf{X}_{blf} + \mu_{i,\tau(l)} + \theta_{i,t} + \gamma_f + \delta_b + \psi_{\text{type}(l)} + \varepsilon_{blfi,t}.\end{aligned} \tag{4}$$

$\mu_{i,\tau(l)}$ denotes industry-by-origination-year fixed effects, absorbing all industry-specific conditions at the time the loan is underwritten. $\theta_{i,t}$ represents industry-by-calendar-year fixed effects, capturing time-varying industry conditions in the year the default status is measured. Because the outcome varies within a facility across calendar years, $\mu_{i,\tau(l)}$ and $\theta_{i,t}$ are separately identified: the former holds the underwriting environment fixed while the latter absorbs the realized industry conditions that generate defaults. γ_f and δ_b denote borrower and bank fixed effects, respectively, while

$\psi_{\text{type}(l)}$ controls for loan type.

This specification compares loans made within the same industry and origination year by banks with different degrees of specialization, while controlling for persistent borrower and bank heterogeneity. The coefficient of interest, β_3, captures whether loans extended by specialized banks to their preferred industries in the first post-runup year are associated with differential ex post default risk relative to loans extended by nonspecialized banks to the same industry at the same time. Given the loan-year structure, β_3 is the differential probability that a facility is in default status in a given year of exposure, not the differential probability that it ever defaults. Two features of this estimand are worth making explicit. First, it is exposure-weighted rather than facility-weighted: a facility outstanding for seven years contributes seven observations and a facility outstanding for two contributes two, so longer-maturity loans receive proportionally more weight.[6] Second, because a borrower in prolonged distress registers a one in each year the loan remains outstanding, the measure reflects both the incidence and the persistence of default. Standard errors are clustered at the bank level.

Table 2 shows that loans issued by specialized banks to their preferred industries in the first post-runup year are in default status in 0.621 percentage points more of their exposure years than comparable loans issued by nonspecialized banks. Given a sample mean loan-year default rate of 4.91%, this corresponds to approximately a 13 percent increase in default likelihood. The inclusion of borrower, bank, loan-type, and multiple layers of industry fixed effects indicates that this pattern is not driven by industry-wide demand shifts or persistent differences across banks and firms. In short, when specialized banks lend into their preferred industries in the year following a runup,

[6]Table 1 reports loan maturity by bank type; the two groups are similar, so the exposure weighting is unlikely to drive the results.

they originate loans that subsequently fail at a meaningfully higher rate than comparable loans made by nonspecialized banks.

4.4 Contract Terms at Origination

The default results raise the question of whether specialized banks anticipate the elevated risk of loans originated in the first post-runup year and adjust contract terms accordingly. If the elevated default rate were simply a consequence of compensated risk-taking (specialized banks knowingly extending riskier loans, but charging more or demanding more collateral in exchange), the conventional informational view would still survive. To examine this contracting margin, I estimate:

$$\begin{aligned} y_{blfi} = {} & \beta_1 \text{Specialized Bank}_{blfi} + \beta_2 \text{Runup}_{i,\tau(l)} \\ & + \beta_3 \big(\text{Specialized Bank}_{blfi} \times \text{Runup}_{i,\tau(l)}\big) \\ & + \mathbf{X}_{blf} + \mu_{i,\tau(l)} + \gamma_f + \delta_b + \psi_{\text{type}(l)} + \varepsilon_{blfi}, \end{aligned} \tag{5}$$

where the dependent variable y_{blfi} corresponds to alternative loan characteristics at origination: the all-in spread drawn (AISD), an indicator for collateralization, or the log loan amount.

Across specifications (Table 3), the interaction between specialization and runups does not show consistent evidence of tighter contract terms. While the AISD and loan amount interactions are marginally significant, the signs are in the wrong direction. Specialized banks appear to charge lower spreads and issue larger loans in the first post-runup year, and there is no significant effect on collateralization.[7] Taken together, the evidence does not support the interpretation that specialized banks anticipate elevated risk and price it into contract terms at origination.

[7]The loan amount interaction is the least stable of the three: it reverses sign under the stacked design of Section 8, where it is -0.100 rather than 0.053, with both estimates marginally significant. The absence of tightening on spreads and collateral holds in both designs; the direction of the loan-size response does not.

The patterns in this section are difficult to reconcile with the standard interpretation of bank specialization as a source of superior information. Industry profitability, equity returns, and debt growth all decline from their runup-period peaks in the years that follow (Section 4.1); yet specialized banks expand their commercial lending and reduce provisioning during the runup years in which their preferred industry's stock price is appreciating (Section 4.2); the loans they originate in the first post-runup year default at materially higher rates than comparable loans made by nonspecialized banks (Section 4.3); and they do not compensate by tightening loan terms at origination (Section 4.4). On a simple informational view, in which specialized banks better understand the industries they lend to, they should be less prone, not more, to overextending credit in the kind of period whose favorable conditions are, on average, about to revert toward the mean. The next section proposes an explanation for this pattern that takes both the average informational advantage and the cyclical reversal seriously.

5 Diagnostic Expectations & Bank Specialization

The patterns documented in Section 4 are puzzling under a fully rational view of bank specialization: specialized banks, who are supposed to know their industries best, originate the loans that later perform worst in precisely the industries whose signals were strongest. I propose an explanation that retains the standard informational advantage of specialized banks but lets both bank types update their beliefs in a behaviorally biased way, in the spirit of the diagnostic expectations framework of Bordalo et al. (2018, 2020).

The economics is simple. A specialized bank concentrates its attention and lending on a single industry and therefore observes a more precise signal about that industry's fundamentals; a diversified bank spreads its attention across many sectors and observes a noisier signal about any one of them (Blickle et al., 2026, 2025). Both banks share the same degree of diagnostic overreaction. The specialized bank's sharper signal leads it to place more weight on incoming news, and the shared diagnostic distortion amplifies that greater responsiveness: applied to a larger updating gain, the same overweighting factor produces more extreme beliefs. During a runup the specialized bank therefore overreacts more, becomes more optimistic about its industry, and lends on looser terms than its diversified peer. The model delivers two implications that I take to the data: specialized banks should hold systematically more optimistic beliefs about their industries during runups, and the effect should be larger in opaque industries, where specialization confers the greatest informational advantage.

5.1 Setup

There is a single industry, whose fundamental x_t follows an AR(1) process:

$$x_t = \rho\, x_{t-1} + \varepsilon_t, \qquad \varepsilon_t \sim \mathcal{N}(0, \sigma_\varepsilon^2), \qquad |\rho| < 1. \tag{6}$$

Signals. Two banks observe noisy signals of the fundamental that differ in precision:

$$s_t^S = x_t + \eta_t^S, \quad \eta_t^S \sim \mathcal{N}(0, \sigma_S^2), \qquad s_t^D = x_t + \eta_t^D, \quad \eta_t^D \sim \mathcal{N}(0, \sigma_D^2), \qquad \sigma_S^2 < \sigma_D^2, \tag{7}$$

with measurement noise independent across banks and over time, and orthogonal to the fundamental x_t and its innovations ε_t.

Banks. The two banks differ only in the precision of the signal they receive:

- **Specialized bank** S: concentrates on the industry and observes the precise signal s_t^S (low noise σ_S^2), reflecting its focused attention, deeper relationships, and industry-specific expertise.

- **Diversified bank** D: spreads attention across many sectors and observes the noisier signal s_t^D (high noise σ_D^2) about this industry.

I take specialization, and the resulting signal precision, as exogenously given. Because the fundamentals of other industries carry no information about x_t, the diversified bank's other lending plays no role in its beliefs about this industry and need not be modeled explicitly: diversification enters solely through the reduced precision of the own-industry signal. This is consistent with the relationship-lending literature, which emphasizes that proprietary information is produced as a byproduct of concentrated, repeated engagement with a sector and is not freely available to less-focused lenders (Sharpe, 1990; Petersen and Rajan, 1994).

A natural concern with this modeling choice is that it appears to claim that specialized banks, which tend to be smaller than diversified lenders, possess intrinsically superior information about their industry of focus, so that, to take an extreme case, a regional bank is presumed to understand pharmaceutical lending better than a global institution such as JPMorgan. My argument does not require this interpretation. The precision ordering $\sigma_S^2 < \sigma_D^2$ need not capture the raw quality of information an institution could in principle assemble; it can instead represent the bank's ability to act on the information it receives. Following Stein (2002), the capacity to act on information—especially the soft, sector-specific information most relevant during an industry runup—depends on organizational form. In a large, hierarchical lender, information about a given industry is produced by agents with limited incentive to generate it and then transmitted upward to those with capital-allocation authority; because soft information is difficult to communicate credibly across layers of an organization, much of it is attenuated in transit.

A specialized bank faces this friction to a lesser degree. In Stein (2002), what discourages information production is the risk that capital will be redirected to another division on the basis of that division's prospects rather than one's own, so that the information an agent has gathered is never put to use. A diversified bank, even one that is organizationally flat, still faces this risk, because it must allocate capital across competing industries. Because a specialized bank lends to fewer industries, there are fewer competing claims on its capital, the incentive to produce industry information is preserved, and the signal reaches the lending decision largely intact. Read this way, the assumption $\sigma_S^2 < \sigma_D^2$ need not imply any informational deficiency at large banks; it can instead reflect the lower organizational barriers a specialized lender faces in converting what it observes into a lending decision. This reinterpretation leaves the model's mechanics and predictions unchanged and is consistent with my central result: because a specialized bank can act on its industry signal with little organizational friction, it overreacts most under diagnostic expectations, and this overreaction is why its loans perform worse than those of diversified lenders when it specializes in an industry undergoing a runup.

5.2 Rational Updating

Each bank forms beliefs about x_t with a univariate Kalman filter on its own signal. I analyze a single episode, taking as the starting point a belief about x_{t-1} that the two banks hold in common.

Assumption 1 (Common prior at the start of the episode). *At the end of period $t-1$ both banks hold the same belief about the fundamental, $x_{t-1} \mid \mathcal{I}_{t-1} \sim \mathcal{N}(\mu_{t-1}, P_{t-1})$, with μ_{t-1} and P_{t-1}*

common across banks. Private signals s_t^S and s_t^D arrive only in period t.

This is the natural benchmark for the experiment the model is designed to capture. The question is how two banks that begin from the same view of an industry diverge once each processes its own signal about a runup, so the informational asymmetry is deliberately confined to the current signal rather than to accumulated belief histories. Absent Assumption 1 the two banks would differ both in signal precision and in inherited priors, and the resulting belief gap would confound the specialization channel with path dependence in beliefs, which is not the mechanism I take to the data.

Under Assumption 1 the one-step-ahead prior variance of x_t is common to both banks and equal to

$$p \;\equiv\; \rho^2 P_{t-1} + \sigma_\varepsilon^2, \tag{8}$$

so that $p = \sigma_\varepsilon^2$ in the special case where x_{t-1} is commonly known ($P_{t-1} = 0$). Define the signal innovation $\Delta s_t^j \equiv s_t^j - \rho\mu_{t-1}$ for bank $j \in \{S, D\}$, which is likewise measured from a common prior mean. The Kalman gains are:

$$K_S = \frac{p}{p + \sigma_S^2}, \qquad K_D = \frac{p}{p + \sigma_D^2}, \qquad K_S > K_D, \tag{9}$$

where the ordering follows immediately from $\sigma_S^2 < \sigma_D^2$: the specialized bank places greater weight on its signal because that signal is more precise. The rational posterior means are:

$$\mu_t^{S,B} = \rho\mu_{t-1} + K_S\,\Delta s_t^S, \qquad \mu_t^{D,B} = \rho\mu_{t-1} + K_D\,\Delta s_t^D. \tag{10}$$

5.3 Diagnostic Expectations

Following Bordalo et al. (2018) and Bordalo et al. (2020), agents overweight signal innovations by a multiplicative factor $(1+\theta)$ with $\theta > 0$. Both banks share the same distortion θ. The diagnostic posterior means are:

$$\mu_t^S = \rho\mu_{t-1} + (1+\theta)\, K_S\, \Delta s_t^S, \qquad \mu_t^D = \rho\mu_{t-1} + (1+\theta)\, K_D\, \Delta s_t^D, \tag{11}$$

and the diagnostic overreaction in each bank's belief is the wedge between its diagnostic and rational posterior:

$$\Omega_t^S \equiv \mu_t^S - \mu_t^{S,B} = \theta\, K_S\, \Delta s_t^S, \qquad \Omega_t^D \equiv \mu_t^D - \mu_t^{D,B} = \theta\, K_D\, \Delta s_t^D. \tag{12}$$

5.4 Relative Overreaction

The difference in overreaction between the two banks is:

$$\Omega_t^S - \Omega_t^D = \theta\big(K_S\, \Delta s_t^S - K_D\, \Delta s_t^D\big)\,. \tag{13}$$

Both banks observe the same underlying fundamental, so conditioning on x_t and writing the common fundamental innovation $g_t \equiv x_t - \rho\mu_{t-1}$, the expected signal innovations are equal, $\mathbb{E}[\Delta s_t^j \mid x_t] = g_t$, and the relative overreaction reduces to a function of the gain gap alone:

$$\mathbb{E}\big[\Omega_t^S - \Omega_t^D \,\big|\, x_t\big] = \theta\,(K_S - K_D)\, g_t = \theta\, \frac{p\,(\sigma_D^2 - \sigma_S^2)}{(p+\sigma_S^2)(p+\sigma_D^2)}\, g_t. \tag{14}$$

This is the central result of the model. Relative overreaction is governed by the precision gap between the two banks, scaled by the fundamental innovation g_t and the distortion θ. The fraction is strictly positive whenever $\sigma_D^2 > \sigma_S^2$.

Proposition 1 (Industry Runup)**.** *Suppose the industry experiences a positive innovation, $g_t = x_t - \rho\mu_{t-1} > 0$. Then $\mathbb{E}[\Omega_t^S \mid x_t] > \mathbb{E}[\Omega_t^D \mid x_t] > 0$.*

Both banks overreact, but the specialized bank does so more. The channel is the higher Kalman gain $K_S > K_D$: because the specialized bank trusts its more precise signal, the diagnostic amplification $(1+\theta)K_S$ applied to a positive innovation exceeds the diversified bank's $(1+\theta)K_D$. Expertise generates greater rational responsiveness, which the diagnostic distortion then compounds; overconfidence in a superior information source and diagnostic overreaction reinforce one another. Through the screening mechanism documented in Section 4.3, this greater optimism translates into looser terms and worse subsequent loan performance during runups, even as the specialist's sharper signal makes it the better lender on average.

5.5 Industry Opacity

The size of the relative overreaction depends on how much sharper the specialized bank's signal is than the diversified bank's. I now show that this gap widens with industry opacity, delivering the second empirical implication.

Opacity captures how difficult an industry is to evaluate from public, hard information. A diversified bank, relying on such information, sees its signal degrade as an industry becomes more opaque; a specialized bank draws on relationship- and monitoring-based information produced through concentrated engagement, which is far less sensitive to public disclosure. I formalize this by letting the diversified bank's signal noise rise with opacity $\omega \geq 0$ while the specialist's relationship-based precision is insulated:

$$\sigma_S^2 \text{ fixed}, \qquad \sigma_D^2(\omega) = \sigma_S^2 + \omega, \qquad \omega \geq 0. \tag{15}$$

Opacity is then the entire source of the precision gap: transparent industries ($\omega = 0$) leave the two banks equally informed, and more opaque industries open a wider gap.[8] Substituting (15) into (14) gives the differential overreaction as a function of opacity,

$$\Delta(\omega) \;\equiv\; \mathbb{E}\big[\Omega_t^S - \Omega_t^D \,\big|\, x_t\big] \;=\; \theta\, \frac{p\,\omega}{(p+\sigma_S^2)(p+\sigma_S^2+\omega)}\, g_t. \tag{16}$$

Proposition 2 (Industry Opacity)**.** *Fix a runup, $g_t > 0$. The differential overreaction (16) is strictly increasing in opacity,*

$$\frac{\partial \Delta(\omega)}{\partial \omega} = \theta\, \frac{p\, g_t}{(p+\sigma_S^2+\omega)^2} > 0, \tag{17}$$

with $\Delta(0) = 0$ and $\Delta(\omega) \uparrow \theta\, K_S\, g_t$ as $\omega \to \infty$. The specialized bank's excess overreaction during runups is therefore zero in fully transparent industries and largest in the most opaque ones.

Proof. Differentiate (16) with respect to ω, treating p, σ_S^2, θ, and g_t as fixed; the numerator simplifies to $\theta p g_t$ and the sign is positive. The boundary values follow by evaluating (16) at $\omega = 0$ and taking $\omega \to \infty$, where $p\omega/[(p+\sigma_S^2)(p+\sigma_S^2+\omega)] \to p/(p+\sigma_S^2) = K_S$. $\square$

The result is globally monotone: the wedge rises smoothly with opacity and has no interior turning point. Its magnitude is bounded by the specialist's own diagnostic reaction $\theta K_S g_t$, the level it

[8] Retaining a baseline gap in transparent industries, $\sigma_D^2(\omega) = \sigma_{D0}^2 + \omega$ with $\sigma_{D0}^2 > \sigma_S^2$, only shifts the intercept: the comparative static in Proposition 2 is unchanged because $\partial\sigma_D^2/\partial\omega = 1$ either way.

would reach if the diversified bank were completely uninformed. The mechanism is that a more opaque industry lowers the diversified bank's gain K_D while leaving the specialist's gain K_S intact, so the diversified bank revises its beliefs less and the specialized bank's relative overreaction grows.

Remark 1 (The role of insulation). Monotonicity relies on the specialist's information being insulated from opacity. If the specialist's own precision also degraded with opacity—$\sigma_S^2(\omega) = \sigma_0^2 + \varphi\,\omega$ with $\varphi \in (0, 1)$—the differential would instead be hump-shaped, rising for moderate opacity and eventually falling as both banks become uninformed. The clean, monotone opacity prediction is thus a testable consequence of the assumption that specialization produces relationship-based information that public-disclosure opacity does not erode.

Remark 2 (Empirical implication). Propositions 1 and 2 together imply that the specialized bank's runup optimism, and hence its relative underperformance in subsequent loan defaults, should be concentrated in opaque industries and smallest in transparent ones. In a loan-level specification this is a positive coefficient on the triple interaction *Specialized* $\times$ *Runup* $\times$ *Opacity*, with opacity proxied by the scarcity of public hard information. I take this prediction to the data in Section 6.2.

Carrying these belief results over to loan outcomes requires two steps that the model does not derive. A bank that is more optimistic about an industry lends more to it, extending credit to borrowers it would otherwise decline; and because the borrowers admitted at the margin are of lower quality than those already approved, a larger belief distortion maps into a higher realized default rate. Section 4.4 provides the corresponding empirical check: specialized banks do not offset the additional risk through tighter contract terms.

6 Tests of the Mechanism

Among the empirical implications of the model in Section 5, I focus on two that distinguish a diagnostic-expectations explanation from a purely informational one. First, specialized banks should express systematically more optimistic beliefs about their preferred industries during runups, and this differential should be concentrated in the runup window itself rather than reflecting a permanent disposition. Second, because the specialized bank's informational advantage is greatest when an industry is hard to evaluate from public information, the differential overreaction by specialized banks should be larger in more opaque industries, where the diversified bank's signal degrades but the specialist's relationship-based signal does not. I test each of these predictions in turn.

6.1 Bank Sentiment Toward Preferred Industries

To capture the forward-looking beliefs of specialized lenders, I construct a measure of industry-specific sentiment from bank earnings calls. For each earnings call in my sample, I extract the text of executive turns, comments from the CEO, CFO, and other named officers, using speaker-role classifications from the Capital IQ transcripts database. Analyst questions and responses are excluded to isolate the views expressed by bank management.

I measure sentiment using Llama 3.3 70B, a large language model, run at temperature zero to ensure replicability. For each earnings call, I provide the model with the executive-turn text and ask it to score the bank's expressed sentiment toward each industry it discusses on a continuous scale from -1 (strongly negative) to $+1$ (strongly positive), based solely on language indicating optimism or pessimism about industry credit conditions, loan demand, and borrower quality. I conduct one inference call per earnings call so that the model evaluates each industry in the context of the full call.

I aggregate the resulting scores to the bank $\times$ year $\times$ two-digit SIC level by averaging across the four calendar quarters. Before imposing any threshold, the raw panel spans 63 unique banks and 4,407 bank $\times$ year $\times$ industry cells. On average, a bank discusses 7.2 industries per year (median: 8), indicating that earnings calls provide broad cross-industry coverage. To reduce noise from cells driven by only one or two transcripts, I retain a cell only if the bank discusses the industry in at least three distinct transcripts in that calendar year. This threshold eliminates 1,254 cells, roughly 28 percent of the raw panel, leaving 3,153 qualifying cells across 61 banks. After the filter, banks discuss an average of 5.7 industries per year (median: 6), indicating that the threshold removes thinner-coverage industry-year pairs while preserving the core specialization discussions.

Because the paper's primary hypothesis concerns beliefs about the industries banks specialize in, I further restrict the sentiment sample to cases where the industry being discussed matches the bank's primary specialty. For non-specialized banks, sentiment toward any qualifying industry enters the sample. After these filters, sentiment scores are moderately positive and similar across bank types. Non-specialized banks have a mean score of 0.19 (standard deviation 0.35; 10th–90th percentile range -0.25 to 0.62) and specialized banks have a mean of 0.17 (standard deviation 0.36; range -0.31 to 0.59). The near-identical unconditional means indicate that any differential sentiment between bank types is concentrated in specific episodes rather than in the overall level, which motivates the event-time analysis below.

I merge the sentiment panel to the loan-level data. To estimate the event-time profile of sentiment around industry runups, I employ a stacked regression design. For each runup episode, defined as a unique (industry, cohort year) pair in which the industry-level runup indicator equals one, I construct a clean sub-dataset pairing the runup industry with a set of control industries that have no runup during the event window $[k = -5, k = +1]$ surrounding that cohort. Stacking these sub-datasets avoids the contaminated comparisons that arise in standard staggered designs when an already-treated industry serves as a control for a newly-treated one. I then estimate:

$$\begin{aligned}\text{Sentiment}_{b,i,t,c} = \gamma\big(&\text{Specialized Bank}_b \times \text{Treated}_{i,c}\big) \\ &+ \sum_{k \neq -4} \delta_k \big(\text{Specialized Bank}_b \times \text{Treated}_{i,c} \times \mathbf{1}[k_{t,c} = k]\big) \\ &+ \alpha_b + \mu_{i,t,c} + \varepsilon_{b,i,t,c}, \end{aligned} \tag{18}$$

where $\text{Treated}_{i,c} = 1$ if industry i is the runup industry for cohort c and zero for clean control industries, and $\mathbf{1}[k_{t,c} = k]$ indicates that observation (t, c) falls at event time k relative to the first post-runup year. α_b denotes bank fixed effects, absorbing permanent differences in communication style across banks. $\mu_{i,t,c}$ denotes cohort $\times$ industry $\times$ year fixed effects, absorbing any industry-year-specific sentiment shocks within each cohort's comparison window. Because $\text{Treated}_{i,c}$ is constant within each cohort-industry pair, its main effect is absorbed by $\mu_{i,t,c}$; the coefficients of interest, δ_k, are identified from within-cohort-industry-year variation across bank types: whether specialized banks deviate from the cell mean sentiment more than non-specialized banks do, and whether that deviation is concentrated in the runup industry relative to control industries at each event time. Standard errors are clustered by bank, and the reference period is $k = -4$, the year before the runup begins. The final sample covers 49 banks across 32 industries over 2007–2018.

The estimated interaction coefficients are plotted in Figure 8 and the full results can be found in Table A.3. At $k = -3$, the first year of the runup period, the interaction coefficient turns positive and statistically significant (0.054), indicating that specialized banks express meaningfully more favorable sentiment toward their preferred industry, relative to the pre-runup baseline at $k = -4$, precisely when the runup begins. This is reassuring for the validity of my runup measure: the onset of the credit expansion, as identified by the stock-return-based runup indicator, coincides with a meaningful divergence in the industry beliefs of specialized versus non-specialized lenders. The coefficient on Specialized Bank is positive but noisy, indicating no robust unconditional sentiment premium after conditioning on bank and industry-year fixed effects. In the post-runup period, the interaction coefficient at $k = 0$ is negative and statistically significant (-0.055), and the coefficient at $k = +1$ remains negative (-0.033) though no longer statistically significant, indicating that specialized banks express comparatively less favorable sentiment than non-specialized banks in the years immediately following the runup peak. Taken together, this pattern is consistent with specialized banks having expressed elevated optimism during the runup itself, with the differential reversing once the runup ends: relative to the pre-runup baseline at $k = -4$, specialized banks become more positive than non-specialized banks during the runup and then more negative once the runup concludes. The sentiment evidence supports the model's first prediction: specialized banks' beliefs diverge from those of non-specialized banks around credit cycle turning points, and the divergence is concentrated precisely where the model says it should be.

6.2 Industry Opacity

The model's second prediction is that the differential overreaction by specialized banks during runups should be stronger in more opaque industries. Intuitively, a diversified bank relies on public, hard information, so its signal degrades as an industry becomes harder to evaluate, whereas a specialized bank draws on relationship- and monitoring-based information that public-disclosure opacity does not erode; the precision gap between the two therefore widens with opacity. I exploit cross-industry variation in valuation opacity to test this implication. I construct *Low Rating Coverage*, an indicator equal to one if credit rating coverage in an industry-year falls below the cross-sectional median. I then augment Equation 4 with interactions between *Low Rating Coverage*, *Specialized Bank*, and *Runup*.

The triple-interaction coefficient is positive and economically large (Table 4): the specialization–runup differential is -0.534 in high-coverage industries and 0.853 in low-coverage ones, the latter significantly positive. The increase in default risk associated with specialization in the first post-runup year is substantially stronger in industries with lower information coverage. Importantly, Table 5 shows that specialized banks in these opaque industries do not significantly tighten pricing or collateral requirements in these years. These patterns line up with the model: the differential is larger precisely where the specialized bank's informational advantage is greatest, and is not absorbed by compensating adjustments on the observable contract terms. The results are also harder to reconcile with explanations based solely on contracting frictions or observable risk adjustments.

7 Alternative Explanations

The combination of bank-level lending behavior, loan-level default risk, sentiment, and opacity heterogeneity is consistent with the diagnostic expectations mechanism developed in Section 5. To strengthen this interpretation, I now consider three alternative explanations that could in principle generate higher default rates among specialized banks during industry runups without invoking belief distortions: industry capture and rent-seeking, geographic clustering and local economic conditions, and relationship lending. I show that none of these channels can account for the observed patterns, and that a final test isolating loans within versus outside the bank's preferred industry further sharpens the case for an industry-specific belief-formation mechanism.

7.1 Industry Capture

One alternative explanation for the higher default rate of loans issued by specialized banks during industry runups is that specialization reflects market power within a sector rather than informational advantage. Highly specialized banks often have a large share of their capital invested in a single industry, potentially giving them market power within that sector. Banks that capture an industry may use their position to extract rents from captive borrowers, and this incentive may be especially strong during industry runups, when heightened lending competition depresses loan profits (see Dinç, 2000). To test this channel directly, I incorporate *Industry Capture* into the baseline regression with a full set of interactions. If industry capture is the operative channel, the triple interaction should absorb the *Specialized Bank* $\times$ *Runup* effect.

I define industry capture as the squared share of syndicated loans issued to industry i by bank b at time t, that is, Industry Capture$_{b,i,t} = s^2_{b,i,t}$, where $s_{b,i,t}$ is bank b's share of total syndicated loan volume to industry i in year t, with volumes measured as estimated retained exposures throughout (Section 3.2). This measure is equivalent to bank b's individual contribution to the industry-level Herfindahl-Hirschman Index (HHI), and captures the degree to which a single bank dominates lending to a given sector. HHI is a relatively common measure of competition. As such, the degree to which a single bank affects the competitiveness of an industry is a good measure of the degree to which it has captured that industry. An industry with only one bank will be perfectly captured by that bank. Similar to my measure of *Specialization* discussed above, the measure is continuous and bounded between 0 and 1, making it easy to interpret. There exists a high degree of correlation between industry capture and specialization. However, given that these industries are defined at the two-digit SIC code, they are quite large, especially for the industries most banks specialize in. As a consequence, even large banks can specialize without necessarily capturing an industry.

The results of this exercise are reported in column (3) of Tables 6 and 7. Once the full interaction set is included, the *Specialized Bank* $\times$ *Runup* coefficient is no longer an average effect: it is the effect evaluated at zero industry capture. It remains positive and statistically significant at 1.021, so the elevated default rates of specialized banks are present among loans to industries in which the bank holds no market position of consequence, and industry capture cannot account for them. The triple interaction *Specialized Bank* $\times$ *Runup* $\times$ *Industry Capture* is -0.839. The estimate is too imprecise to be informative.

7.2 Geographic Specialization and Relationship Lending

I next address two additional sources of informational advantage that could potentially explain the observed patterns without appealing to belief distortions. First, specialization may in part reflect geographic clustering, whereby banks concentrated in certain regions lend disproportionately to locally dominant industries. If geographic proximity confers informational advantages (e.g., Berger et al. 2005; Loutskina and Strahan 2011), or if local economic conditions move together with industry runups (e.g Peek and Rosengren 2000; Gilje et al. 2016), then geographic co-location rather than industry experience could drive the results. Second, relationship lending can generate borrower-specific knowledge that is distinct from industry-level expertise. A large literature has documented that relationship lenders may be willing to accept short-term losses to preserve ongoing lending relationships (see, e.g., Sharpe 1990; Petersen and Rajan 1994; Drucker and Puri 2005; Bharath et al. 2011). If the elevated default rates I document simply reflect this kind of relationship-preserving behavior, the behavioral interpretation would be less compelling.

To test these channels, I estimate two further variants of the baseline specification in Equation 4, each augmented with the full set of interactions for one alternative variable. I construct a *State* indicator equal to one if the bank's and borrower's headquarters are located in the same state, capturing the geographic co-location channel, and a *Relationship* indicator equal to one if the bank and borrower have previously interacted, capturing borrower-specific knowledge from prior dealings. If either channel drives the result, its triple interaction with *Specialized Bank* and *Runup* should absorb the *Specialized Bank* $\times$ *Runup* effect.

The results are reported in columns (1) and (2) of Tables 6 and 7. As before, the *Specialized Bank* $\times$ *Runup* coefficient is a conditional effect: it applies to loans that lack the interacted feature, namely loans to borrowers the bank has not previously lent to in column (1) and to borrowers headquartered outside the bank's state in column (2). It remains positive and statistically significant in both, with point estimates of 0.603 and 0.607, close to the baseline of 0.621. The differential default risk of specialized banks during runups therefore persists among loans that neither proxy captures and cannot be attributed wholly to relationship lending or geographic proximity. The triple interactions themselves are 0.287 for *Relationship* and -0.374 for *State*, neither precise enough to establish whether the differential differs within the proxied groups.

To further examine whether the elevated default rates of specialized banks in the first post-runup year reflect a general tendency to lend more aggressively, or whether this behavior is specific to their preferred industries, I reintroduce loans made by specialized banks to non-preferred industries and construct an indicator variable, *Focal Loan*, equal to one if the loan is made to the bank's top industry. I then re-estimate the baseline specification with a triple interaction between *Specialized Bank*, *Runup*, and *Focal Loan*. As reported in Tables A.6 and A.7, the higher ex post default rates of specialized banks in the first post-runup year are concentrated in loans made to their preferred industries. There is no evidence that specialized banks systematically make riskier loans outside of their preferred industries, nor do they adjust loan characteristics ex ante in anticipation of these outcomes. This pattern is difficult to reconcile with a pure relationship or geographic story, and instead points to industry-specific belief formation as the operative mechanism.

Taken together, the alternative-explanation tests reinforce the case for the diagnostic-expectations interpretation: the runup-period excess defaults among specialized banks persist among loans that industry capture, geographic co-location, and borrower-specific relationship lending do not account for, and they are confined to the very industries in which specialized banks build up the most concentrated information set.

8 Robustness

To verify the robustness of the main findings, I estimate several variations of the baseline specification in Equation 4. In Table A.8, instead of using the Murfin (2012) definition of default, I proxy for financial distress using Altman Z-scores (Altman, 1968) and predicted probabilities of financial distress from Campbell et al. (2008). Because a higher Altman Z-score indicates lower distress while a higher CHS probability indicates greater distress, the two measures carry opposite signs; both point in the same direction as the baseline.

I also vary the cutoff thresholds used to define *Specialized Bank* and *Runup*. Tables A.9 and A.10 report results using a specialization threshold of 30% rather than the baseline 20% while Tables A.11 and A.12 report results using a runup threshold of 15% cumulative excess returns rather than the baseline 20%. Across all threshold variations, the main findings remain intact.

A further concern is that the baseline specialization measure, the share of a bank's lending concentrated in its single largest industry, takes no account of how large that industry is within the overall syndicated loan market. Because syndicated lending is unevenly distributed across industries, a bank can appear concentrated merely by participating heavily in an industry that draws a large volume of credit, even when its allocation is no greater than what a broadly diversified lender would hold. To address this, I re-estimate the main specifications using the excess specialization measure of Blickle et al. (2026), which benchmarks a bank's allocation to an industry against that industry's share of aggregate syndicated lending. For bank b, industry i, and year t, define

$$e_{b,i,t} = \frac{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{b,i,\tau}}{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{b,\tau}} - \frac{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{i,\tau}}{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{\tau}}, \tag{19}$$

where the first term is the fraction of bank b's syndicated lending directed to industry i and the second is industry i's share of all syndicated lending, both accumulated over the same five-year lookback window used in the baseline measure. The quantity $e_{b,i,t}$ measures the deviation of the bank's portfolio from a diversified benchmark that holds each industry at its market weight: it is positive when the bank is over-invested in industry i relative to that benchmark, negative when under-invested, and bounded in neither direction. A bank that channels 15% of its syndicated lending to the oil and gas industry over a window in which that industry accounts for 6% of all syndicated lending carries an excess specialization of nine percentage points there, whereas the baseline share measure would record the full 15%.

Blickle et al. (2026) adopt this difference-based construction in preference to a ratio-based alternative that scales over-investment by industry size. A ratio measure generates a long right tail, since a bank holding 10% of its portfolio in an industry accounting for 1% of aggregate lending registers as over-invested by a factor of ten. The difference measure treats a given percentage-point deviation identically regardless of the industry's market weight, which discards information about relative magnitudes but is far less prone to tail-driven artifacts.

The measure is aggregated to the bank level exactly as in the baseline. For each bank-year I take the industry in which excess specialization is highest, and *Specialized Bank* equals one when that maximum falls in the top quartile of the pooled bank-year distribution and zero otherwise. The industry attaining the maximum becomes the bank's preferred industry for the robustness exercise, and because benchmarking against aggregate lending can reorder a bank's industries, it need not be the industry holding the largest raw lending share; focal-loan and runup-exposure assignments are recomputed accordingly. Since both terms are accumulated over $t-5$ through $t-1$, the classification excludes year-t originations, as in the baseline. Tables A.13 and A.14 report the resulting estimates for borrower default and loan characteristics, respectively, and the runup-period default differential and loan-term results remain qualitatively and quantitatively consistent with the baseline findings.

To address concerns regarding biases arising from staggered runup timing, I employ a stacking methodology for the loan-level analyses. This approach constructs cohort-specific samples around each runup event, comparing units experiencing a runup to units that are not currently in a runup and have not experienced one in the previous five years. The cohorts are then combined into a single stacked regression framework. The results of this exercise are reported in Tables A.15, A.16, and A.17. The default results are robust to the stacked design. In Table A.15 the *Specialized Bank* $\times$ *Runup* coefficient retains its sign, significance, and approximate magnitude, and The opacity heterogeneity also survives: the triple interaction in Table A.17 is 2.149, comparable to the baseline 1.387. The stacked design is far less precise about the level of the differential within low-coverage industries, which is distinguishable neither from zero nor from its baseline counterpart.

The contract-term estimates in Table A.16 are less stable. The interaction on log loan amount is 0.053 in the baseline of Table 3 and -0.100 under stacking, with both marginally significant, so the sign of the quantity response is not robust to the choice of comparison group. The spread interaction remains negative but is no longer statistically significant, and the collateral interaction is insignificant in both designs with a sign change. What survives across both designs is the absence of tightening: in neither specification do specialized banks charge significantly higher spreads or require significantly more collateral on runup-period loans in their preferred industry, which is what the argument in Section 4.4 relies on.

Overall, the loan-level evidence indicates that during industry runups, specialized banks extend credit that subsequently performs worse relative to comparable loans made by nonspecialized banks, without offsetting adjustments in the price or collateralization of those loans.

9 Conclusion

Industry profitability, equity returns, and debt growth all decline, on average, from their stock-market runup peaks in the years that follow, yet the banks that should be best positioned to recognize this risk, those most specialized in the relevant industry, do not pull back. Instead, they expand their commercial lending and reduce loan-loss provisions during the runup years in which their preferred industry's stock price is appreciating, and the loans they originate in the first post-runup year default at rates approximately 13 percent higher than comparable loans made by nonspecialized banks to the same industry. They do not compensate by tightening loan terms. The cross-sectional evidence that specialization confers an informational advantage, which I confirm in the data, thus appears to invert during industry-level cycles.

I argue that this state-contingent reversal reflects a difference in how specialized and diversified banks update beliefs, not a difference in their underlying screening technology. A model in the spirit of Bordalo et al. (2020) formalizes the idea: because specialized banks observe a more precise signal about their focal industry, they place more weight on favorable own-industry news, and the shared diagnostic distortion amplifies this greater responsiveness into stronger overreaction. Among the model's empirical implications, I focus on two that the data support: specialized banks express significantly more positive sentiment toward their preferred industries during runups, with the differential concentrated in the runup window, and the runup-period excess default rate of specialized banks is substantially larger in industries with sparser information coverage.

A series of alternative explanations cannot account for the patterns. Industry capture, geographic clustering, and prior lending relationships each leave the runup-period default differential essentially unchanged, and the higher default risk is concentrated entirely in loans that specialized banks make to their preferred industry. The mechanism is industry-specific, consistent with industry-specific belief formation rather than a general appetite for risk.

Together, these results highlight that industry specialization, typically associated with informational advantages and enhanced monitoring capacity, can also foster biased expectations during boom periods, particularly when it reinforces prevailing optimism in expanding industries. They imply that the cross-sectional benefits of specialization impose additional costs during sections of the lending cycle, and that organizational structure shapes belief formation in ways that propagate through credit markets.

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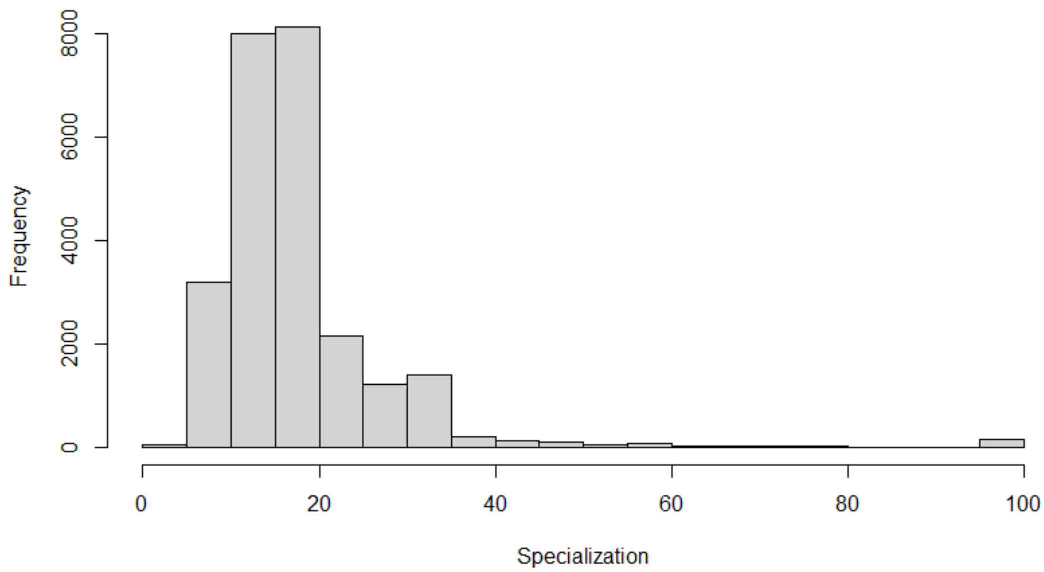

Figure 1: Distribution of Specialization

This graph shows the distribution of specialization across all loan observations in the sample. Specialization is the loan concentration in a bank's top industry over the previous five years

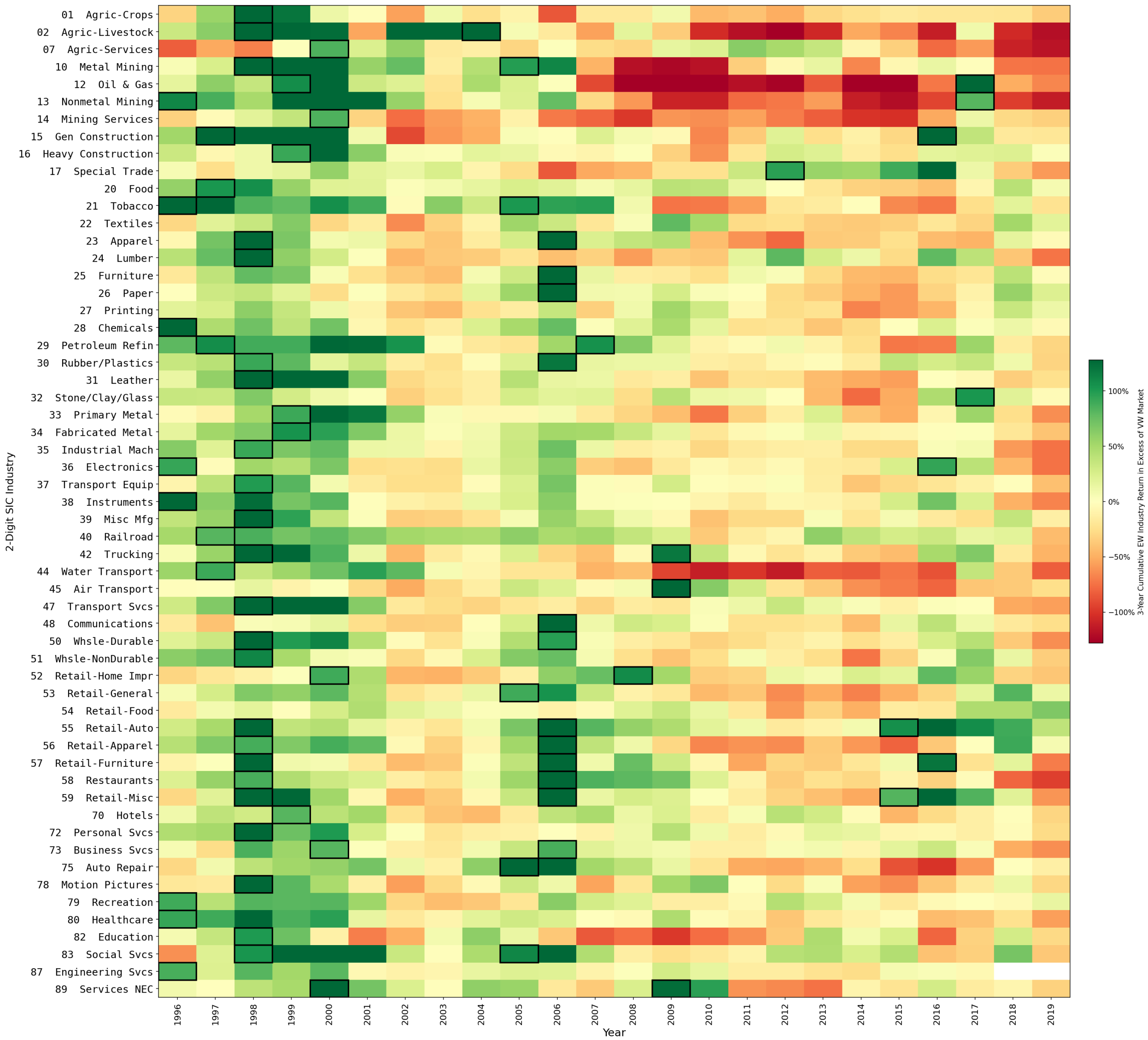

Figure 2: Industry Runup Classification

This figure maps the industry runup classification across the sample period. Each cell corresponds to a two-digit SIC industry (rows) in a given year (columns) and is shaded by the industry's three-year cumulative equal-weighted return in excess of the value-weighted market, with greener cells denoting stronger industry outperformance and redder cells weaker performance. Cells outlined in black mark the industry-years classified as runups, that is, those with a three-year cumulative excess return of at least 20%, subject to a positive raw three-year return and the five-year exclusion window described in Section 3.4. The identified runups cluster in the late 1990s, the mid-2000s, and the early-to-mid 2010s.

Table 1: Summary Statistics by Bank Type and Loan Characteristics

This table provides summary statistics for several key variables used in the analysis. Specialization is the proportion of loans made by the bank to the top industry over the previous five-year period. Ln(Amount) is the natural log of the loan amount. Size is the natural log of the book value of banks' total assets. Tier 1 Capital Ratio is the ratio of banks' tier 1 capital to their total adjusted risk-weighted assets. Profitability is the ratio of net income to book value of total assets. Age is measured as the current date minus the first date in Compustat. Credit Rating is a series of categorical variables for S&P credit ratings. Secured is an indicator variable equal to 1 if the loan is secured with collateral and 0 otherwise. Syndicate size is the number of lenders. Maturity is the loan maturity in months. Mean diff is the p-value for the two-sided t-test. The Wilcoxon p-value is the p-value for each variable X, the distribution between specialized and nonspecialized banks is the same (Wilcoxon, 1945). *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

	Nonspecialized				Specialized				All Banks				Differences	
Variable	N	Mean	SD	Med.	N	Mean	SD	Med.	N	Mean	SD	Med.	Mean Diff (p-value)	Wilcoxon
Panel A: Bank Characteristics														
Specialization (%)	18,187	13.61	3.34	14.25	5,792	33.90	16.80	28.05	23,979	18.51	12.33	15.42	$<0.001^{***}$	$<0.001^{***}$
Bank size	18,157	8.23	1.71	8.17	5,781	7.88	1.89	7.88	23,938	8.15	1.76	8.11	$<0.001^{***}$	$<0.001^{***}$
Ln(Amount)	18,187	3.64	1.18	3.69	5,792	3.19	1.22	3.21	23,979	3.53	1.20	3.58	$<0.001^{***}$	$<0.001^{***}$
Tier 1 Capital Ratio	17,904	10.53	2.57	10.40	4,805	10.37	2.88	10.10	22,709	10.50	2.64	10.40	0.000^{***}	$<0.001^{***}$
Panel B: Borrower Characteristics														
Borrower size	18,187	13.67	1.11	14.12	5,767	12.61	1.52	12.74	23,954	13.41	1.30	13.92	$<0.001^{***}$	$<0.001^{***}$
Leverage (%)	18,131	22.36	6.83	22.14	5,708	18.61	7.99	16.88	23,839	21.46	7.29	21.30	$<0.001^{***}$	$<0.001^{***}$
Profitability (%)	18,187	3.46	8.65	4.20	5,767	2.74	9.26	3.72	23,954	3.04	8.75	4.15	$<0.001^{***}$	$<0.001^{***}$
Credit Rating	18,187	15.51	7.62	13.00	5,792	16.19	7.71	14.00	23,979	15.67	7.64	14.00	$<0.001^{***}$	$<0.001^{***}$
Age	18,187	45.60	12.50	48.00	5,785	26.75	13.80	30.00	23,972	41.06	15.15	43.00	$<0.001^{***}$	$<0.001^{***}$
Panel C: Loan Characteristics														
AISD (%)	16,422	1.71	1.18	1.50	5,076	1.76	1.27	1.50	21,498	1.72	1.20	1.50	0.002^{***}	0.126
Secured (%)	11,304	62.41	48.44	100.00	3,311	70.13	45.78	100.00	14,615	64.16	47.95	100.00	$<0.001^{***}$	$<0.001^{***}$
Syndicate Size	18,187	9.58	7.58	8.00	5,792	9.62	8.12	7.00	23,979	9.59	7.71	8.00	0.738	0.008^{***}
Maturity	17,531	49.03	22.39	60.00	5,554	49.78	25.72	60.00	23,085	49.21	23.24	60.00	0.035^{**}	0.299

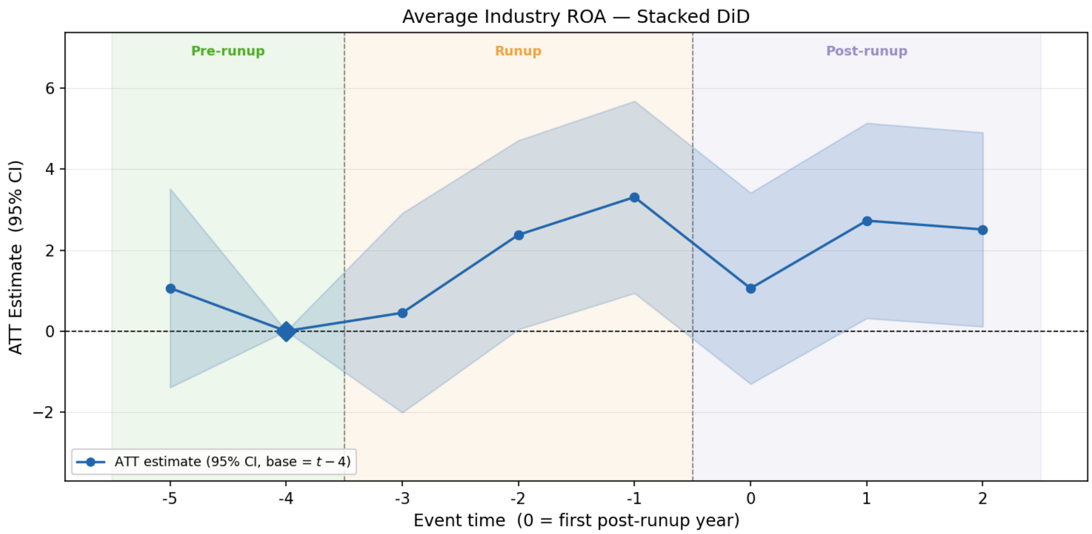

Figure 3: Industry ROA

Coefficients from a stacked difference-in-differences event study estimated over the period 1996–2019. The outcome variable is industry return on assets (ROA), expressed in percentage points. The specification includes stack-by-industry and stack-by-year fixed effects. Standard errors are clustered at the industry level.

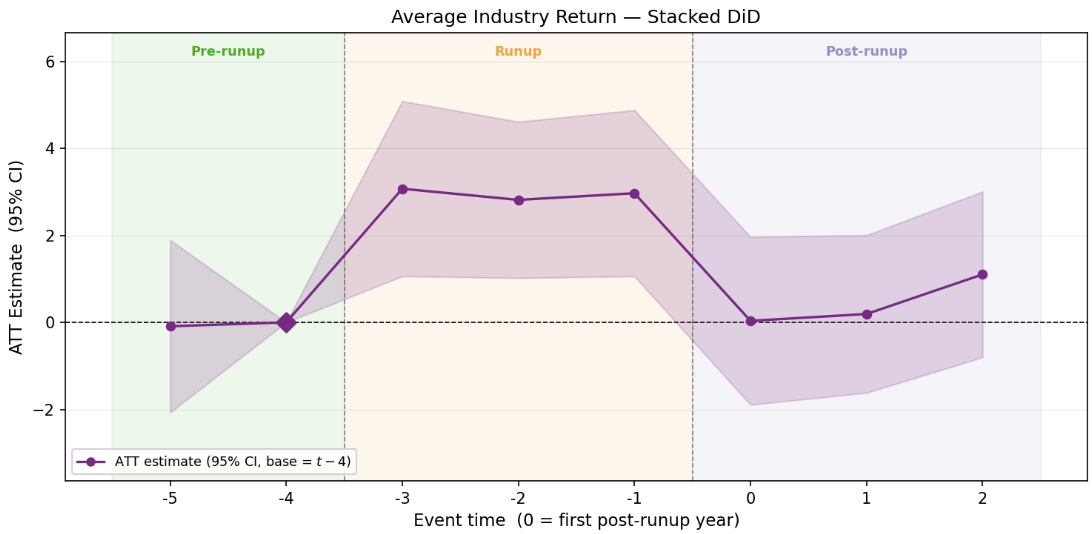

Figure 4: Industry Return

Coefficients from a stacked difference-in-differences event study estimated over the period 1996–2019. The outcome variable is the raw equal-weighted industry stock return, expressed in percentage points. The specification includes stack-by-industry and stack-by-year fixed effects. Standard errors are clustered at the industry level.

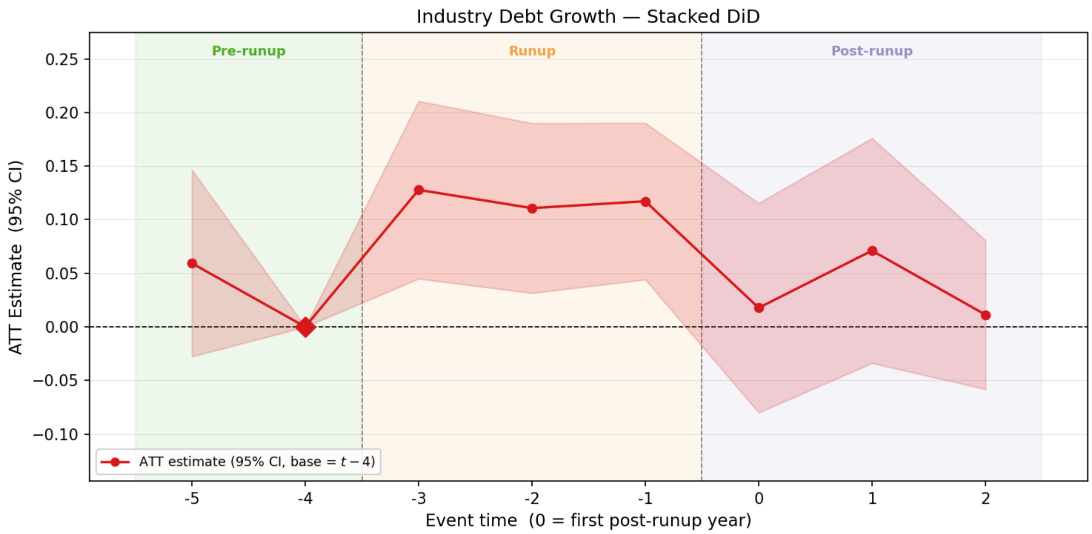

Figure 5: Industry Debt Growth

Coefficients from a stacked difference-in-differences event study estimated over the period 1996–2019. The outcome variable is year-over-year log growth in total industry debt. The specification includes stack-by-industry and stack-by-year fixed effects. Standard errors are clustered at the industry level.

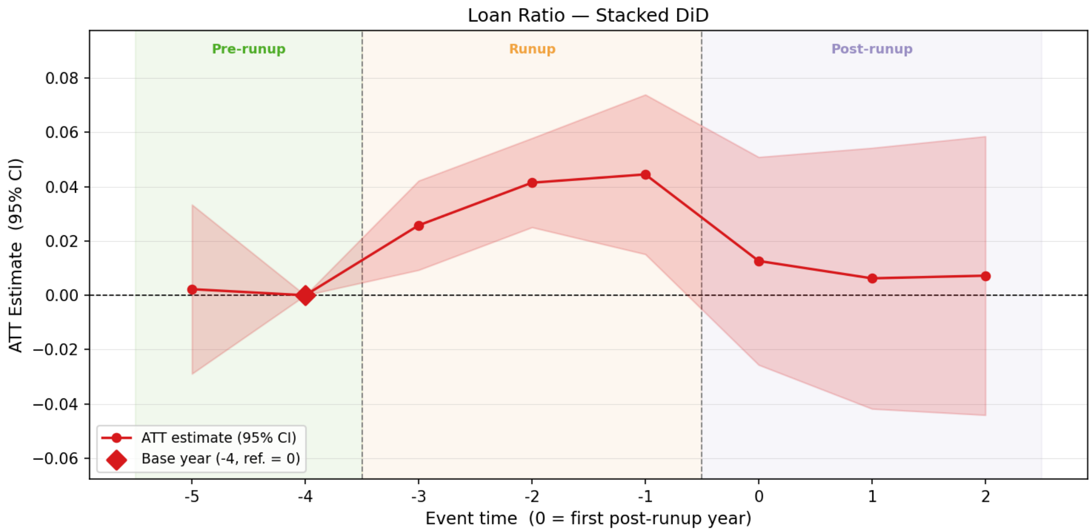

Figure 6: Bank Loan Ratio

The figure plots coefficients on the interaction of event-time indicators and the treated-bank indicator from a stacked difference-in-differences event study estimated over the period 1996–2019. The outcome variable is the total C&I lending over total assets. Treated units are specialized banks whose preferred industry experiences a runup; control banks are institutions with no runup in their preferred industry anywhere in the $[-5, +2]$ window. Each coefficient reflects the average treatment effect on the treated (ATT) for specialized banks relative to these unexposed controls and to the year before the runup begins ($k = -4$), with event time $k \in \{-5, -3, -2, -1, 0, +1, +2\}$. Shaded bands denote 95% confidence intervals. Fixed effects include cohort $\times$ bank and cohort $\times$ year. Standard errors are clustered at the bank level.

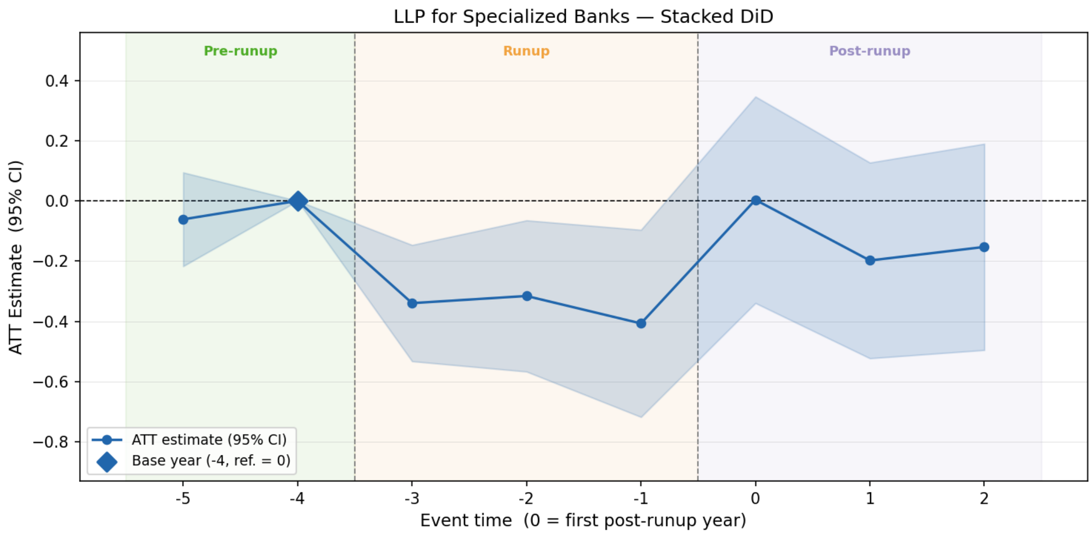

Figure 7: Bank Loan Loss Provisions

The figure plots coefficients on the interaction of event-time indicators and the treated-bank indicator from a stacked difference-in-differences event study estimated over the period 1996–2019. The outcome variable is the loan loss provision ratio over total assets (LLP) multiplied by 100. Treated units are specialized banks whose preferred industry experiences a runup; control banks are institutions with no runup in their preferred industry anywhere in the $[-5, +2]$ window. Each coefficient reflects the average treatment effect on the treated (ATT) for specialized banks relative to these unexposed controls and to the year before the runup begins ($k = -4$), with event time $k \in \{-5, -3, -2, -1, 0, +1, +2\}$. Shaded bands denote 95% confidence intervals. Fixed effects include cohort $\times$ bank and cohort $\times$ year. Standard errors are clustered at the bank level.

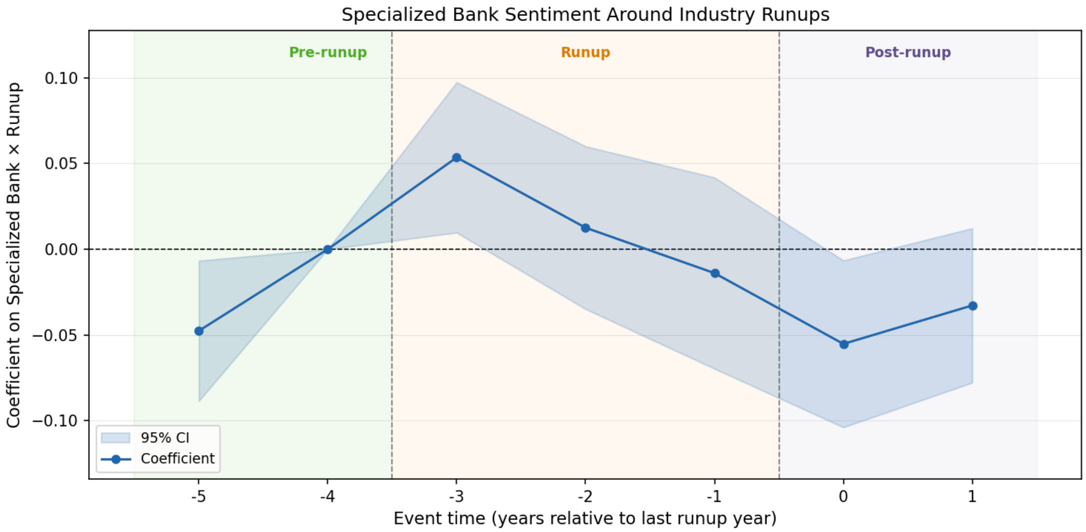

Figure 8: Sentiment

The figure plots the coefficients δ_k from the stacked event-study regression in Equation (18), estimated over the period 2007–2018. Each coefficient captures the differential sentiment expressed by specialized banks toward their preferred industry, relative to non-specialized banks, at event time k around industry runups. The reference period is $k = -4$, the year before the runup begins, with event time $k \in \{-5, -3, -2, -1, 0, +1\}$. Shaded bands denote 95% confidence intervals. Fixed effects include bank and cohort $\times$ industry $\times$ year. Standard errors are clustered at the bank level.

Table 2: Specialization and Default Rates

This table reports the regression results estimating the determinants of borrower default rates on bank type and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution, and 0 otherwise. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. *Default* is an indicator variable that is equal to 1 if the borrower's S&P credit rating is Default or Selective Default in year t and the loan is still outstanding in that year, and 0 otherwise. The unit of observation is the bank–borrower–facility–year: each facility contributes one observation for each calendar year it remains active, so a borrower in prolonged default registers a one in each such year and the estimates are weighted by years of exposure rather than by facility. Industries are identified using the two-digit SIC code. Controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and Tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

	(1) Default	(2) Default	(3) Default	(4) Default	(5) Default
Specialized Bank	-0.163	-0.010	-0.612***	-0.329***	-0.051
	(0.214)	(0.222)	(0.226)	(0.106)	(0.219)
Runup		-0.103*			-0.101*
		(0.056)			(0.055)
Specialized Bank × Runup	0.621***	0.604***	0.514***	0.545***	0.685***
	(0.138)	(0.141)	(0.149)	(0.148)	(0.144)
Bank Size	0.064	0.520***	-0.140	0.058	0.539***
	(0.159)	(0.143)	(0.163)	(0.037)	(0.131)
Tier 1 Capital	-0.011	0.037	-0.013	-0.043	0.025
	(0.031)	(0.025)	(0.033)	(0.028)	(0.024)
Borrower Age	-0.012	-0.005	-0.016***	-0.018***	0.067***
	(0.027)	(0.023)	(0.002)	(0.002)	(0.019)
Borrower Leverage	0.019**	0.021***	0.036***	0.021***	0.026***
	(0.008)	(0.007)	(0.008)	(0.005)	(0.007)
Borrower Profitability	-0.022***	-0.024***	-0.038***	-0.037***	-0.034***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Borrower Size	-0.500***	-0.705***	-0.484***	-0.489***	-0.873***
	(0.073)	(0.072)	(0.029)	(0.028)	(0.065)
Borrower Credit Rating	-1.420***	-1.564***	-0.493***	-0.492***	-1.368***
	(0.021)	(0.021)	(0.013)	(0.013)	(0.019)
Syndicate Size	0.001	0.002	0.018***	0.013***	0.004
	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
Observations	83,926	84,014	83,952	83,956	84,088
Adjusted R^2	0.409	0.302	0.280	0.269	0.247
Industry × Year FE	YES	NO	YES	YES	NO
Industry × Origin Year FE	YES	YES	YES	YES	NO
Bank FE	YES	YES	YES	NO	YES
Borrower FE	YES	YES	NO	NO	YES
Loan Type FE	YES	YES	YES	NO	NO

Table 3: Specialization and Loan Characteristics

This table reports the regression the relationship between specialization and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution, and 0 otherwise. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. *Secured* is an indicator variable that is equal to 1 if the loan is secured with collateral and 0 otherwise. *Ln(Amount)* is the natural log of the loan amount. Industries are identified using the two-digit SIC code. Controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. *AISD* is the all-in drawn spread, measured in basis points. Standard errors clustered at the bank level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

	(1) AISD	(2) Secured	(3) Ln(Amount)
Specialized Bank	-4.839**	-2.400**	0.013
	(2.289)	(1.107)	(0.024)
Specialized Bank × Runup	-5.655*	-1.921	0.053*
	(3.040)	(1.446)	(0.031)
Bank Size	-11.251***	-3.281*	0.115***
	(3.547)	(1.695)	(0.036)
Tier 1 Capital	0.879	-0.138	-0.005
	(0.707)	(0.320)	(0.007)
Borrower Age	-9.594	8.734**	0.006
	(7.199)	(3.848)	(0.072)
Borrower Leverage	-0.033	0.107	0.001
	(0.176)	(0.086)	(0.002)
Borrower Profitability	-2.043***	-0.371***	0.001
	(0.104)	(0.047)	(0.001)
Borrower Size	-8.107***	-5.970***	0.339***
	(1.364)	(0.671)	(0.014)
Borrower Credit Rating	0.810***	-0.220***	0.005***
	(0.163)	(0.083)	(0.002)
Syndicate Size	-2.077***	-0.543***	0.002**
	(0.098)	(0.050)	(0.001)
Observations	19,855	13,619	22,098
Adjusted R^2	0.663	0.698	0.595
Mean	1.72	64.16	3.53
Industry × Year FE	YES	YES	YES
Bank FE	YES	YES	YES
Borrower FE	YES	YES	YES
Loan Type FE	YES	YES	YES

Table 4: Loan Default: Opaque Industry Analysis

This table reports the regression results estimating the determinants of borrower default rates on bank type, industry opacity, and loan characteristics during periods of industry run-ups in the stock market. The full sample covers the years 1996–2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution, and 0 otherwise. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. *Default* is an indicator variable that is equal to 1 if the borrower's S&P credit rating is Default or Selective Default in year t and the loan is still outstanding in that year and 0 otherwise. Industries are identified using the two-digit SIC code. *Low Rating Coverage* is an indicator variable that equals 1 if, in a given year, an industry falls below the cross-sectional median of credit rating coverage. Controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and tier 1 capital ratio. All variable definitions can be found in Table IA.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. * p<0.1, ** p<0.05, *** p<0.01.

	(1) Default
Specialized Bank	−0.497**
	(0.246)
Specialized Bank × Runup	−0.534***
	(0.205)
Specialized Bank × Low Rating Coverage	0.491
	(0.311)
Specialized Bank × Runup × Low Rating Coverage	1.387***
	(0.294)
Bank Size	−0.098
	(0.173)
Tier 1 Capital	−0.049
	(0.033)
Borrower Age	-0.018
	(0.031)
Borrower Leverage	0.028***
	(0.008)
Borrower Profitability	0.017***
	(0.005)
Borrower Size	−0.508***
	(0.076)
Borrower Credit Rating	−1.489***
	(0.022)
Syndicate Size	0.004
	(0.003)
Observations	83,926
Adjusted R^2	0.402
Industry × Origin Year FE	YES
Industry × Year FE	YES
Bank FE	YES
Borrower FE	YES
Loan Type FE	YES

Table 5: Loan Outcomes: Specialized Banks, Runups, and Low Rating Coverage

This table reports the regression the relationship between specialization, industry opacity, and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. The full sample covers the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution, and 0 otherwise. *Runup* is an indicator variable that is equal to 1 equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. Default is an indicator variable that is equal to 1 if the borrower's S&P credit rating is Default or Selective Default in year t and the loan is still outstanding in that year and 0 otherwise. Industries are identified using the two-digit SIC code. *Low Rating Coverage* is an indicator variable that equals to 1 if, in a given year, an industry falls below the cross-sectional median of credit rating coverage. For brevity, coefficient estimates for other control variables are omitted, however controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

	(1) AISD	**(2)** Secured	**(3)** Ln(Amount)
Specialized Bank	−0.167	1.549	0.149
	(0.121)	(5.529)	(0.112)
Specialized Bank × Runup	0.060	−5.284	0.060
	(0.116)	(5.759)	(0.109)
Specialized Bank × Low Rating Coverage	0.044	4.294	0.123
	(0.108)	(4.849)	(0.102)
Specialized Bank × Runup × Low Rating Coverage	−0.203	−4.305	0.119
	(0.157)	(7.324)	(0.148)
Observations	19,855	13,619	22,098
Adjusted R^2	0.663	0.683	0.573
Controls	YES	YES	YES
Industry × Year FE	YES	YES	YES
Bank FE	YES	YES	YES
Borrower FE	YES	YES	YES
Loan Type FE	YES	YES	YES

Table 6: Loan Defaults: Alternative Channels

This table reports the regression results estimating the determinants of borrower default rates on bank type and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. Each column augments the baseline specification in Equation (4) with the full set of interactions (main effect, two-way interactions with *Specialized Bank* and *Runup*, and the triple interaction) for one alternative channel: relationship lending in column (1), geographic co-location in column (2), and industry capture in column (3). *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution, and 0 otherwise. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. *Default* is an indicator variable that is equal to 1 if the borrower's S&P credit rating is Default or Selective Default in year t and the loan is still outstanding in that year and 0 otherwise. *Relationship* is an indicator variable that is 1 if the bank previously lent to the borrower and 0 otherwise. *State* is an indicator variable that is 1 if the bank is headquartered in the same state as the borrower and 0 otherwise. *Industry Capture* is the squared share of syndicated loans issued to the borrower's industry by the bank, equivalent to the bank's contribution to the industry-level Herfindahl-Hirschman Index. Industries are identified using the two-digit SIC code. For brevity, coefficient estimates for other control variables are omitted; other controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and Tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Default	**(2)** Default	**(3)** Default
Specialized Bank	-0.363	-0.562	-1.058^{*}
	(0.797)	(0.434)	(0.574)
Specialized Bank × Runup	0.603^{**}	0.607^{**}	1.021^{***}
	(0.297)	(0.262)	(0.342)
Relationship	0.068		
	(0.183)		
Specialized Bank × Relationship	-0.260		
	(0.711)		
Runup × Relationship	-0.146		
	(0.286)		
Specialized Bank × Runup × Relationship	0.287		
	(1.053)		
State		0.061	
		(0.190)	
Specialized Bank × State		-0.379	
		(0.512)	
Runup × State		-0.169	
		(0.201)	
Specialized Bank × Runup × State		-0.374	
		(0.663)	
Industry Capture			-0.803
			(0.886)
Specialized Bank × Industry Capture			1.552
			(1.281)
Runup × Industry Capture			0.681
			(0.996)
Specialized Bank × Runup × Industry Capture			-0.839
			(1.526)
Observations	83,926	83,926	83,926
Adjusted R^2	0.405	0.406	0.406
Controls	YES	YES	YES
Industry × Origin Year FE	YES	YES	YES
Industry × Year FE	YES	YES	YES
Bank FE	YES	YES	YES
Borrower FE	YES	YES	YES
Loan Type FE	YES	YES	YES

Table 7: Loan Characteristics: Alternative Channels

This table reports the relationship between specialization and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. Each set of three columns augments the baseline specification with the full set of interactions (main effect, two-way interactions with *Specialized Bank* and *Runup*, and the triple interaction) for one alternative channel: relationship lending, geographic co-location (*State*), and industry capture, in turn. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution, and 0 otherwise. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. *AISD* is the all-in spread drawn, expressed in basis points. *Secured* is an indicator variable equal to 1 if the loan is secured with collateral and 0 otherwise. *Ln(Amount)* is the natural log of the loan amount. *Relationship* is an indicator equal to 1 if the bank previously lent to the borrower. *State* is an indicator equal to 1 if the bank's and the borrower's headquarters are in the same state. *Industry Capture* is the squared share of syndicated loans issued to the borrower's industry by the bank, equivalent to the bank's contribution to the industry-level Herfindahl-Hirschman Index. Industries are identified using the two-digit SIC code. For brevity, coefficient estimates for other control variables are omitted; other controls include borrower, loan, and lender controls. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	AISD			Secured			Ln(Amount)		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Specialized Bank	0.021	0.045	0.136***	−0.551	−1.334	0.794	0.048	0.080**	−0.034
	(0.043)	(0.032)	(0.053)	(2.133)	(1.581)	(2.572)	(0.045)	(0.034)	(0.054)
Specialized Bank × Runup	−0.043	−0.134***	−0.206***	3.788	2.783	3.042	0.014	0.141***	0.129*
	(0.069)	(0.044)	(0.076)	(3.396)	(2.110)	(3.617)	(0.072)	(0.046)	(0.078)
Relationship	0.024			2.794**			0.018		
	(0.023)			(1.109)			(0.024)		
Specialized Bank × Relationship	0.030			−0.268			0.033		
	(0.048)			(2.331)			(0.050)		
Runup × Relationship	0.003			−1.901			−0.002		
	(0.035)			(1.713)			(0.037)		
Specialized Bank × Runup × Relationship	−0.131			−2.226			−0.224***		
	(0.081)			(3.868)			(0.084)		
State		−0.163***			−5.557***			0.258***	
		(0.042)			(2.111)			(0.043)	
Specialized Bank × State		−0.044			3.749			−0.111	
		(0.079)			(3.971)			(0.081)	
Runup × State		0.033			1.254			−0.121**	
		(0.050)			(2.567)			(0.052)	
Specialized Bank × Runup × State		0.027			−2.475			0.100	
		(0.130)			(7.283)			(0.136)	
Industry Capture			0.467***			2.647			−0.447***
			(0.144)			(7.258)			(0.145)
Specialized Bank × Industry Capture			−0.466***			−8.223			0.454**
			(0.177)			(8.656)			(0.178)
Runup × Industry Capture			−0.393**			−5.852			0.251
			(0.174)			(8.303)			(0.176)
Specialized Bank × Runup × Industry Capture			0.508**			2.682			−0.200
			(0.248)			(11.708)			(0.250)
Observations	19,855	19,855	19,855	13,619	13,619	13,619	22,098	22,098	22,098
Adjusted R^2	0.657	0.657	0.657	0.701	0.701	0.701	0.593	0.593	0.593
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry × Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Borrower FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Loan Type FE	YES	YES	YES	YES	YES	YES	YES	YES	YES

Appendix

Appendix A1. Lead Arranger Identification

Identifying the lead arranger(s) from DealScan is not as trivial as it may initially appear. I follow the methodology used by Chakraborty et al. (2018), which is similar to that employed by Bharath et al. (2011).

Sole lender transactions, by construction, have a clearly identified lead bank, and I designate it as such. For syndicated loans, DealScan provides two variables that aid in identifying the lead bank: one is a text variable that defines the lender role, and the other is a yes/no lead arranger credit variable. Chakraborty et al. (2018) develop a ranking hierarchy to determine which bank(s) may be the lead arranger:

1. Lender is denoted as "Admin Agent"
2. Lender is denoted as "Lead Bank"
3. Lender is denoted as "Lead Arranger"
4. Lender is denoted as "Mandated Lead Arranger"
5. Lender is denoted as "Mandated Arranger"
6. Lender is denoted as either "Arranger" or "Agent" and has a "Yes" for the lead arranger credit
7. Lender is denoted as either "Arranger" or "Agent" and has a "No" for the lead arranger credit
8. Lender has a "Yes" for the lead arranger credit but has a role other than those previously listed ("Participant" and "Secondary Investor" are also excluded)
9. Lender has a "No" for the lead arranger credit but has a role other than those previously listed ("Participant" and "Secondary Investor" are also excluded)
10. Lender is denoted as a "Participant" or "Secondary Investor"

For a given loan package, the lender with the highest-ranking title (according to this ten-part hierarchy) is considered the lead agent. In the sample of loans I am able to match to Compustat, roughly 90% of loan packages have at least one bank that falls into one of the first six categories.

Appendix A2. Bank Attrition

There is a fair amount of year-to-year variation in the set of specialized banks. Most of this variation is attributable to banks failing to meet the minimum loan threshold described in Section 3.1, rather than banks losing their specialization status or exiting the DealScan database. As noted above, specialization is persistent: conditional on a bank being identified as specialized, there is a 74% probability that it will remain specialized in the same industry the following year, assuming it continues to operate. Similarly, if a bank is identified as nonspecialized, there is approximately a 90% probability that it will remain nonspecialized in the subsequent year.

Additionally, in the sample that does not restrict to lead banks only, each time a specialized bank is observed in a given year, there is an 87% chance that the same bank is observed again in the following year. This suggests that much of the attrition in the specialized bank sample is driven by the relatively low frequency of specialized banks serving as lead arrangers, rather than bank exit or reclassification.

Table A.1: Variable Definitions

Variable Name	Definition	Source
AISD	The all-in drawn spread, which is the sum of the spread of the facility over LIBOR and any annual fees paid to the lender group (alldrawn). Measured in basis points in the regressions; reported in percentage points in Table 1.	DealScan
Bank Size	The natural log of the book value of total assets (AT).	Compustat
Borrower Age	Current date minus first debt in Compustat.	Compustat
Borrower Book Equity	The ratio of book value of common equity (CEQ) to book value of total assets (AT).	Compustat
Borrower Credit Rating	A series of categorical variables for S&P credit ratings, ex. 1 for "AAA", 2 for "AA", etc.	Compustat
Borrower Leverage	The ratio of long-term liabilities (DLTT) plus current liabilities (DLC) to book value of total assets (AT).	Compustat
Borrower Not Rated	An indicator variable that equals one if the firm has no S&P credit rating and 0 if it does have a rating.	Compustat
Borrower Profitability	The ratio of net income (NI) to book value of total assets (AT).	Compustat
Borrower Size	The natural log of the book value of total assets (AT).	Compustat
Small Industry	An indicator variable that is 1 if the borrower's industry, in a given year, falls below the cross-sectional median of average firm size, and 0 otherwise. Measured at the industry-year level.	CRSP
Low Profit	An indicator variable that is 1 if the borrower's industry, in a given year, falls below the cross-sectional median of industry profitability, and 0 otherwise. Measured at the industry-year level.	CRSP
Low Rating Coverage	An indicator variable that is 1 if the borrower's industry, in a given year, falls below the cross-sectional median of the fraction of firms in the industry holding a credit rating, and 0 otherwise. Measured at the industry-year level.	Compustat
Default	An indicator variable that is 1 if S&P rates the borrower firm as Default (D) or Selective Default (SD) in year t and the loan is still outstanding in that year, and 0 otherwise.	Compustat
Ln(Amount)	The natural logarithm of the bank's estimated retained exposure to the loan, constructed following Blickle et al. (2020) as described in Section 3.2.	DealScan, SNC
Loan Loss Provisions	Total loan loss provisions divided by total assets multiplied by 100.	FR-Y9C
Loan Type	A series of categorical variables for loan type buckets. 1 for term A loans, 2 for lower tranche term loans (b, c, d, etc.), 3 for other term loans where the tranche is not defined, 4 for credit lines, and 5 for all other loans.	DealScan
Loan Ratio	The ratio of total commercial and industrial loan volume (LCACLD) divided by total assets (AT).	Compustat
Maturity	The maturity of the loan in months (maturity).	DealScan
Runup	An indicator variable that is 1 if the column's industry average three-year stock return in excess of the market $\geq 20\%$ and 0 otherwise.	CRSP
Secured	An indicator variable that is 1 if the loan is secured and 0 otherwise.	DealScan
Specialization	For each bank, specialization is the amount invested in the bank's top industry over the previous five years divided by all loans made by the bank over the same five years.	DealScan
Specialized Bank	An indicator variable that is 1 if Specialization is $\geq 20\%$ and 0 otherwise.	DealScan
Syndicate Size	The number of syndicate members.	DealScan
Tier 1 Capital Ratio	The ratio of banks' tier 1 capital and its total adjusted risk-weighted assets (CAPR1).	Compustat

Table A.2: Sample Distribution

This table describes the observations used in the paper. Columns (1) and (2) are measured at the bank–year level: column (1) reports the number of unique banks appearing in the sample each year, and column (2) the number of those banks classified as specialized in that year. A bank is specialized in year t if its five-year lending concentration in a single industry falls in the top quartile of the pooled bank–year distribution, a cutoff corresponding to a concentration share of approximately 20% (Section 3.3). Columns (3) through (7) are measured at the bank–borrower–facility level. Column (3) reports the total number of loans originated each year. Columns (4) and (5) report loans originated by specialized banks to their preferred (focal) industry and to all other industries; columns (6) and (7) report the corresponding counts for nonspecialized banks. Columns (4) through (7) sum to column (3) by construction.

Year	(1) Total Banks	(2) Specialized Banks	(3) Total Loans	(4) Spec Loans Focal Ind.	(5) Spec Loans Non-Focal Ind.	(6) Nonspec Loans Focal Ind.	(7) Nonspec Loans Non-Focal Ind.
1996	31	7	560	116	64	44	336
1997	36	9	749	142	71	64	472
1998	37	10	737	198	91	58	390
1999	37	10	862	163	86	48	565
2000	38	11	1,031	162	99	69	701
2001	40	11	1,069	162	105	76	726
2002	41	11	1,055	172	96	84	703
2003	40	9	961	70	69	94	728
2004	39	8	1,067	70	69	91	837
2005	37	8	1,097	130	100	83	784
2006	38	8	1,051	168	105	79	699
2007	35	8	993	164	107	67	655
2008	30	7	533	70	58	37	368
2009	30	7	399	64	58	25	252
2010	34	9	728	87	68	55	518
2011	31	9	1,162	291	108	69	694
2012	29	6	993	107	74	84	728
2013	31	9	1,266	153	121	78	914
2014	30	8	1,299	163	99	117	920
2015	33	8	1,315	124	112	116	963
2016	30	6	1,188	171	95	94	828
2017	30	8	1,307	226	111	73	897
2018	30	7	1,365	189	112	117	947
2019	33	10	1,192	241	111	72	768
Total	820	204	23,979	3,603	2,189	1,794	16,393

Table A.3: Specialized Bank Sentiment Around Industry Runups.

This table reports estimates from a stacked regression examining bank–industry sentiment around stock market runups over the period 2007–2018. *Specialized Bank* is an indicator equal to one if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution. *Runup* is an indicator equal to one if the equal-weighted industry excess return over the three years prior to loan origination is greater than or equal to 20%. *Sentiment* is the four-quarter average of a measure ranging from [-1, 1], constructed from the tone of banks' quarterly earnings calls using a large language model. Industries are defined at the 2-digit SIC level. The specification includes event-time indicators relative to the year before the runup begins (reference period $t = -4$), along with bank fixed effects and cohort-by-industry-by-year fixed effects. Standard errors clustered at the bank level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

	(1) Sentiment
Runup$_{t-5}$ × Specialized Bank	-0.048^{**}
	(0.021)
Runup$_{t-4}$ × Specialized Bank	0
	(ref.)
Runup$_{t-3}$ × Specialized Bank	0.054^{**}
	(0.022)
Runup$_{t-2}$ × Specialized Bank	0.013
	(0.024)
Runup$_{t-1}$ × Specialized Bank	-0.014
	(0.028)
Runup$_{t}$ × Specialized Bank	-0.055^{**}
	(0.025)
Runup$_{t+1}$ × Specialized Bank	-0.033
	(0.023)
Specialized Bank	0.035
	(0.049)
Observations	1,168
Adjusted R^2	0.711
Bank FE	Yes
Cohort × Industry × Year FE	Yes

Table A.4: Industry-Level Event Study: Runups and Outcomes

This table summarizes industry outcomes around stock market runup events over the period 1996–2019. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return over the three years before year t is greater than or equal to 20% and 0 otherwise. Industries are defined using 2-digit SIC. The dependent variables are the industry-level average of ROA, year-over-year log debt growth, and equal-weighted stock returns. Event-time (lead/lag) dummies relative to the year before the runup begins ($t-4$) are included; $t-4$ is the omitted reference period. The specification is estimated using a cohort difference-in-differences design and includes cohort-by-industry and cohort-by-year fixed effects. Standard errors clustered by industry are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

	(1) ROA	**(2)** Debt Growth	**(3)** Return
Runup_{t-5}	1.064	0.059	-0.089
	(1.253)	(0.044)	(1.011)
Runup_{t-4} (ref.)	0	0	0
Runup_{t-3}	0.451	0.128^{***}	3.072^{***}
	(1.257)	(0.042)	(1.027)
Runup_{t-2}	2.377^{**}	0.111^{***}	2.816^{***}
	(1.191)	(0.040)	(0.916)
Runup_{t-1}	3.310^{***}	0.117^{***}	2.969^{***}
	(1.210)	(0.037)	(0.975)
Runup_{t}	1.055	0.018	0.035
	(1.204)	(0.050)	(0.984)
Runup_{t+1}	2.728^{**}	0.071	0.192
	(1.230)	(0.054)	(0.924)
Runup_{t+2}	2.510^{**}	0.011	1.102
	(1.223)	(0.035)	(0.972)
Observations	29,031	28,722	26,607
Adjusted R^2	0.808	0.192	0.459
Cohort $\times$ Industry FE	YES	YES	YES
Cohort $\times$ Year FE	YES	YES	YES

Table A.5: Bank-Level Event Study: Loan Loss Provisions and Lending

This table summarizes bank loan loss provisions and lending behavior around stock market runups during the years 1996–2019. *Specialized Bank* is an indicator variable equal to one if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution, and zero otherwise. *Runup* is an indicator variable equal to one if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and zero otherwise. *LLP* is loan loss provisions divided by total assets multiplied by 100. *Loan Ratio* is total C&I loan volume divided by total assets. Industries are defined using 2-digit SIC. Event-time (lead/lag) dummies relative to the year before the runup begins ($t-4$) are included; $t-4$ is the omitted reference period. The specification is estimated using a cohort difference-in-differences design and includes cohort-by-bank and cohort-by-year fixed effects. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

	(1) LLP	(2) Loan Ratio
Runup$_{t-5}$	-0.061	0.002
	(0.079)	(0.016)
Runup$_{t-4}$ (ref.)	0	0
Runup$_{t-3}$	-0.340^{***}	0.026^{***}
	(0.099)	(0.008)
Runup$_{t-2}$	-0.316^{**}	0.041^{***}
	(0.128)	(0.008)
Runup$_{t-1}$	-0.407^{**}	0.045^{***}
	(0.159)	(0.015)
Runup$_{t}$	0.003	0.013
	(0.175)	(0.020)
Runup$_{t+1}$	-0.198	0.006
	(0.166)	(0.024)
Runup$_{t+2}$	-0.153	0.007
	(0.175)	(0.026)
Observations	20,559	14,813
Adjusted R^2	0.674	0.881
Cohort $\times$ Bank FE	YES	YES
Cohort $\times$ Year FE	YES	YES

Table A.6: Loan Default: Focal Industry Analysis

This table reports the regression results estimating the determinants of borrower default rates on bank type and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. *Default* is an indicator variable that is equal to 1 if the borrower's S&P credit rating is Default or Selective Default in year t and the loan is still outstanding in that year and 0 otherwise. *Focal Loan* is an indicator variable which equals 1 if the loan was made to the bank's industry of specialization and 0 otherwise. Industries are identified using the two-digit SIC code. For brevity, coefficient estimates for other control variables are omitted, however other controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and Tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Default
Specialized Bank	−0.262
	(0.330)
Focal Loan	−0.210
	(0.144)
Specialized Bank × Focal Loan	−0.290
	(0.445)
Specialized Bank × Runup	−0.283
	(0.249)
Focal Loan × Runup	−0.618***
	(0.186)
Specialized Bank × Focal Loan × Runup	1.778***
	(0.530)
Observations	93,926
Adjusted R^2	0.410
Controls	YES
Industry × Origin Year FE	YES
Industry × Year FE	YES
Bank FE	YES
Borrower FE	YES
Loan Type FE	YES

Table A.7: Loan Characteristics: Focal Industry Analysis

This table reports the relationship between specialization and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution, and 0 otherwise. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. *Secured* is an indicator variable that is equal to 1 if the loan is secured with collateral and 0 otherwise. *Focal Loan* is an indicator variable that equals 1 if the loan was made to the bank's industry of specialization and 0 otherwise. *Ln(Amount)* is the natural log of the loan amount. Industries are identified using the two-digit SIC code. For brevity, coefficient estimates for other control variables are omitted, however other controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and Tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10%, respectively.

	(1) AISD	**(2)** Secured	**(3)** $\ln$(Amount)
Specialized Bank	0.005	−5.987***	0.018
	(0.038)	(1.859)	(0.039)
Focal Loan	−0.037	3.348**	0.164***
	(0.029)	(1.435)	(0.030)
Specialized Bank × Focal Loan	−0.070	−10.261***	0.234***
	(0.065)	(3.268)	(0.067)
Specialized Bank × Runup	−0.042	2.775	−0.010
	(0.056)	(2.574)	(0.056)
Focal Loan × Runup	−0.028	4.292**	0.051
	(0.042)	(2.063)	(0.043)
Specialized Bank × Focal Loan × Runup	0.068	−2.069	0.142
	(0.098)	(4.713)	(0.100)
Observations	23,855	15,619	25,098
Adjusted R^2	0.663	0.699	0.597
Controls	YES	YES	YES
Industry × Year FE	YES	YES	YES
Bank FE	YES	YES	YES
Borrower FE	YES	YES	YES
Loan Type FE	YES	YES	YES

Table A.8: Alternative Measures of Default Risks

This table reports the regression results estimating the determinants of expected default rates on bank type and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution, and 0 otherwise. $Runup$ is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. $Altman$ is the Altman Z-score (Altman, 1968) of the borrowing firm in year t. CHS 3 is the three-year predicted probability of default using the model and coefficients provided by Campbell et al. (2008), in percentage points, measured in year t. The unit of observation is the bank–borrower–facility–year: each facility contributes one observation for each calendar year it remains active, and both distress measures are recomputed annually. Industries are identified using the two-digit SIC code. For brevity coefficients on controls are omitted however controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10%, respectively.

	(1) Altman	**(2)** CHS 3
Specialized Bank	−0.238**	0.099***
	(0.070)	(0.018)
Specialized Bank × Runup	−0.078*	0.040***
	(0.044)	(0.010)
Bank Size	−0.050	−0.026**
	(0.032)	(0.008)
Tier 1 Capital	−0.011*	−0.005**
	(0.006)	(0.001)
Borrower Leverage	0.079**	0.005**
	(0.001)	(0.001)
Borrower Profitability	−0.677**	0.072**
	(0.012)	(0.003)
Borrower Size	−0.003**	0.001***
	(0.001)	(0.000)
Borrower Credit Rating	−0.001	0.001***
	(0.001)	(0.000)
Observations	76,957	86,292
Adjusted R^2	0.751	0.698
Industry × Origin Year FE	YES	YES
Industry × Year FE	YES	YES
Bank FE	YES	YES
Borrower FE	YES	YES
Loan Type FE	YES	YES

Table A.9: Loan Defaults: Alternative Specialized Bank Cutoff

This table reports the regression results estimating the determinants of borrower default rates on bank type and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank has at least 30% of their loan portfolio concentrated in a single industry over the previous five years. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. *Default* is an indicator variable that is equal to 1 if the borrower's S&P credit rating is Default or Selective Default in year t and the loan is still outstanding in that year and 0 otherwise. Industries are identified using the two-digit SIC code. Controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and Tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Default
Specialized Bank	0.226
	(0.137)
Specialized Bank × Runup	0.687***
	(0.173)
Bank Size	0.052
	(0.158)
Tier 1 Capital	−0.003
	(0.031)
Borrower Leverage	0.020**
	(0.008)
Borrower Profitability	0.022***
	(0.004)
Borrower Size	−0.498***
	(0.073)
Borrower Credit Rating	−1.425***
	(0.021)
Syndicate Size	0.001
	(0.004)
Observations	88,399
Adjusted R^2	0.409
Industry × Origin Year FE	YES
Industry × Year FE	YES
Bank FE	YES
Borrower FE	YES
Loan Type FE	YES

Table A.10: Loan Characteristics: Alternative Specialized Bank Cutoff

This table reports the regression the relationship between specialization and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank has at least 30% of their loan portfolio concentrated in a single industry over the previous five years 0 otherwise. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. *Secured* is an indicator variable that is equal to 1 if the loan is secured with collateral and 0 otherwise. *Ln(Amount)* is the natural log of the loan amount. Industries are identified using the two-digit SIC code. Controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10%, respectively.

	(1) AISD	**(2)** Secured	**(3)** ln(Amount)
Specialized Bank	−0.048*	1.084	0.208***
	(0.026)	(1.319)	(0.027)
Specialized Bank × Runup	0.018	−6.052**	−0.038
	(0.038)	(1.859)	(0.039)
Bank Size	−0.103***	−3.571**	0.128***
	(0.035)	(1.691)	(0.036)
Tier 1 Capital	0.003	−0.108	−0.005
	(0.007)	(0.319)	(0.007)
Borrower Age	−0.094	8.544*	0.000
	(0.072)	(3.849)	(0.071)
Borrower Leverage	−0.001	0.117	0.001
	(0.002)	(0.085)	(0.002)
Borrower Profitability	−0.020**	−0.372**	0.001
	(0.001)	(0.047)	(0.001)
Borrower Size	−0.081**	−5.996**	0.337**
	(0.014)	(0.672)	(0.014)
Borrower Credit Rating	0.008**	−0.223**	0.005**
	(0.002)	(0.083)	(0.002)
Syndicate Size	−0.021***	−0.544***	0.002**
	(0.001)	(0.050)	(0.001)
Observations	19,855	13,619	22,098
Adjusted R^2	0.663	0.699	0.596
Industry × Year FE	YES	YES	YES
Bank FE	YES	YES	YES
Borrower FE	YES	YES	YES
Loan Type FE	YES	YES	YES

Table A.11: Loan Defaults: Alternative Runup Cutoff

This table reports the regression results estimating the determinants of borrower default rates on bank type and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 15% and 0 otherwise. *Default* is an indicator variable that is equal to 1 if the borrower's S&P credit rating is Default or Selective Default in year t and the loan is still outstanding in that year and 0 otherwise. Industries are identified using the two-digit SIC code. Controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and Tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1) Default
Specialized Bank	−0.199
	(0.171)
Specialized Bank × Runup	0.669***
	(0.104)
Bank Size	−0.245***
	(0.077)
Tier 1 Capital	0.004
	(0.015)
Borrower Leverage	0.048***
	(0.002)
Borrower Profitability	−0.114***
	(0.029)
Borrower Size	−0.074***
	(0.003)
Borrower Credit Rating	0.002
	(0.002)
Observations	88,399
Adjusted R^2	0.276
Industry × Origin Year FE	YES
Industry × Year FE	YES
Bank FE	YES
Borrower FE	YES
Loan Type FE	YES

Table A.12: Loan Characteristics: Alternative Runup Cutoff

This table reports the regression the relationship between specialization and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution, and 0 otherwise. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 15% and 0 otherwise. *Secured* is an indicator variable that is equal to 1 if the loan is secured with collateral and 0 otherwise. *Ln(Amount)* is the natural log of the loan amount. Industries are identified using the two-digit SIC code. Controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5% and 10%, respectively.

	(1) AISD	**(2)** Secured	**(3)** ln(Amount)
Specialized Bank	−0.012	−8.497***	0.089**
	(0.034)	(1.666)	(0.035)
Specialized Bank × Runup	−0.030	0.675	−0.064
	(0.045)	(2.136)	(0.046)
Bank Size	−0.104***	−2.883*	0.109**
	(0.035)	(1.693)	(0.036)
Tier 1 Capital	0.008	−0.143	−0.005
	(0.007)	(0.319)	(0.007)
Borrower Age	−0.093	3.595*	0.002
	(0.072)	(3.846)	(0.072)
Borrower Leverage	−0.001	0.083	0.002
	(0.002)	(0.086)	(0.002)
Borrower Profitability	−0.020**	−0.370**	0.001
	(0.001)	(0.047)	(0.001)
Borrower Size	−0.081**	−5.977**	0.339***
	(0.014)	(0.671)	(0.014)
Borrower Credit Rating	0.008**	−0.219**	0.005**
	(0.002)	(0.083)	(0.002)
Syndicate Size	−0.021***	−0.547***	0.002***
	(0.001)	(0.050)	(0.001)
Observations	19,855	13,619	22,098
Adjusted R^2	0.663	0.699	0.595
Industry × Year FE	YES	YES	YES
Bank FE	YES	YES	YES
Borrower FE	YES	YES	YES
Loan Type FE	YES	YES	YES

Table A.13: Specialization and Default Rates: Alternative Specification

This table re-estimates the default regressions reported in Table 2 using an alternative measure of bank specialization. Following Blickle et al. (2026), I measure *excess* specialization as the degree to which a bank is over-invested in an industry relative to the market portfolio, computed as the deviation of the bank's portfolio share in industry i from the aggregate portfolio share, $\frac{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{b,i,\tau}}{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{b,\tau}} - \frac{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{i,\tau}}{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{\tau}}$, with both terms accumulated over the same five-year lookback window used in the baseline measure and the bank-level measure taken as the maximum across industries. As in the baseline analysis, *Specialized Bank* is an indicator variable equal to 1 if the bank is in the top quartile of this measure over the previous five years and 0 otherwise. The dependent variable, *Default*, is an indicator equal to 1 if the borrower's S&P credit rating is Default or Selective Default in year t and the loan is still outstanding in that year and 0 otherwise. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. Industries are identified using the two-digit SIC code. Controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and Tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

	(1) Default	(2) Default	(3) Default	(4) Default	(5) Default
Specialized Bank	-0.036	-0.059	0.117	0.210*	-0.038
	(0.091)	(0.106)	(0.114)	(0.116)	(0.082)
Runup		-0.130			-0.109
		(0.116)			(0.117)
Specialized Bank × Runup	0.297***	0.295**	0.230**	0.263**	0.234*
	(0.100)	(0.117)	(0.115)	(0.120)	(0.121)
Bank Size	0.042	0.518**	-0.220	0.069	0.544**
	(0.252)	(0.227)	(0.265)	(0.084)	(0.253)
Tier 1 Capital	-0.007	0.041	-0.005	-0.032	0.024
	(0.047)	(0.040)	(0.084)	(0.067)	(0.042)
Borrower Age	—	-0.006	-0.016***	-0.018***	0.067
		(0.058)	(0.005)	(0.005)	(0.059)
Borrower Leverage	0.020***	0.021*	0.038*	0.025***	0.028**
	(0.006)	(0.012)	(0.020)	(0.009)	(0.013)
Borrower Profitability	-0.023	-0.025*	-0.038	-0.038	-0.034***
	(0.020)	(0.013)	(0.027)	(0.027)	(0.011)
Borrower Size	-0.490	-0.707*	-0.490***	-0.500***	-0.863**
	(0.364)	(0.372)	(0.176)	(0.176)	(0.374)
Borrower Credit Rating	-1.435***	-1.579***	-0.498***	-0.499***	-1.379***
	(0.278)	(0.338)	(0.115)	(0.116)	(0.308)
Syndicate Size	0.001	0.002	0.018***	0.013**	0.004
	(0.004)	(0.005)	(0.006)	(0.006)	(0.007)
Observations	83,926	84,014	83,952	83,956	84,088
Adjusted R^2	0.410	0.303	0.280	0.270	0.248
Industry × Year FE	YES	NO	YES	YES	NO
Industry × Origin Year FE	YES	YES	YES	YES	NO
Bank FE	YES	YES	YES	NO	YES
Borrower FE	YES	YES	NO	NO	YES
Loan Type FE	YES	YES	YES	NO	NO

Table A.14: Specialization and Loan Characteristics: Alternative Specification

This table re-estimates the loan-characteristic regressions reported in Table 3 using an alternative measure of bank specialization. Following Blickle et al. (2026), I measure *excess* specialization as the degree to which a bank is over-invested in an industry relative to the market portfolio, computed as the deviation of the bank's portfolio share in industry i from the aggregate portfolio share, $\frac{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{b,i,\tau}}{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{b,\tau}} - \frac{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{i,\tau}}{\sum_{\tau=t-5}^{t-1} \text{LoanAmt}_{\tau}}$, with both terms accumulated over the same five-year lookback window used in the baseline measure and the bank-level measure taken as the maximum across industries. As in the baseline analysis, *Specialized Bank* is an indicator variable equal to 1 if the bank is in the top quartile of this measure over the previous five years and 0 otherwise. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. *Secured* is an indicator variable that is equal to 1 if the loan is secured with collateral and 0 otherwise. *Ln(Amount)* is the natural log of the loan amount. Industries are identified using the two-digit SIC code. Controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors clustered at the bank level are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

	(1) AISD	(2) Secured	(3) Ln(Amount)
Specialized Bank	0.006	-1.841*	0.004
	(0.027)	(0.987)	(0.015)
Specialized Bank × Runup	-0.058*	1.138	-0.004
	(0.034)	(1.242)	(0.033)
Bank Size	-0.107*	-3.662	0.117**
	(0.055)	(2.292)	(0.048)
Tier 1 Capital	0.008	-0.117	-0.005
	(0.008)	(0.317)	(0.011)
Borrower Age	-0.092	8.384***	0.005
	(0.058)	(2.567)	(0.064)
Borrower Leverage	-0.000	0.123	0.001
	(0.003)	(0.122)	(0.002)
Borrower Profitability	0.020***	0.371***	-0.001
	(0.001)	(0.054)	(0.001)
Borrower Size	-0.082***	-5.983***	0.339***
	(0.023)	(0.811)	(0.025)
Borrower Credit Rating	0.008***	-0.221*	0.005***
	(0.002)	(0.123)	(0.002)
Syndicate Size	-0.021***	-0.543***	0.002
	(0.002)	(0.083)	(0.004)
Observations	19,855	13,619	22,098
Adjusted R^2	0.663	0.698	0.595
Industry × Year FE	YES	YES	YES
Bank FE	YES	YES	YES
Borrower FE	YES	YES	YES
Loan Type FE	YES	YES	YES

Table A.15: Stacked Loan Default

Loan-year-panel stacked difference-in-differences estimating effects of specialization in an industry on loan defaults rates during the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. *Default* is an indicator variable that is equal to 1 if the borrower's S&P credit rating is Default or Selective Default in year t and the loan is still outstanding in that year and 0 otherwise. Industries are identified using the two-digit SIC code. Controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and Tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors double clustered by bank and cohort are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

	(1) Default
Specialized Bank	-0.030
	(0.614)
Specialized Bank × Runup	0.760*
	(0.418)
Bank Size	0.041
	(0.378)
Tier 1 Capital	0.074
	(0.052)
Borrower Age	0.012
	(0.033)
Borrower Leverage	0.025***
	(0.009)
Borrower Profitability	-0.021
	(0.016)
Borrower Size	-0.602***
	(0.226)
Borrower Credit Rating	-1.295***
	(0.215)
Syndicate Size	-0.002
	(0.003)
Observations	5,546,774
Adjusted R^2	0.508
Industry × Cohort Year FE	YES
Bank FE	YES
Borrower FE	YES
Loan Type FE	YES

Table A.16: Stacked Loan Characteristics and Specialized Banks

This table reports the regression the relationship between specialization and loan characteristics during periods of industry runups in the stock market during the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution, and 0 otherwise. *Runup* is an indicator variable that is equal to 1 if the equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. *Secured* is an indicator variable that is equal to 1 if the loan is secured with collateral and 0 otherwise. *Ln(Amount)* is the natural log of the loan amount. Industries are identified using the two-digit SIC code. Controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. *AISD* is the all-in drawn spread, measured in basis points. Standard errors double clustered by bank and cohort are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

	(1) AISD	**(2)** Secured	**(3)** $\ln(\text{amount})$
Specialized Bank	4.823	−5.203*	0.136**
	(5.274)	(3.060)	(0.057)
Specialized Bank × Runup	−3.106	5.600	−0.100*
	(10.187)	(3.448)	(0.058)
Bank Size	−11.372	−3.479	0.104*
	(8.463)	(2.374)	(0.060)
Tier 1 Capital	0.914	−0.172	−0.020*
	(0.786)	(0.348)	(0.010)
Borrower Age	6.148	14.054***	0.113**
	(15.062)	(3.077)	(0.045)
Borrower Leverage	−0.217	0.030	0.004
	(0.412)	(0.133)	(0.003)
Borrower Profitability	−1.936***	−0.327***	−0.003
	(0.294)	(0.092)	(0.002)
Borrower Size	−10.281**	−5.154***	0.325***
	(4.437)	(1.207)	(0.034)
Borrower Credit Rating	1.183***	−0.043	0.010***
	(0.287)	(0.148)	(0.003)
Syndicate Size	−2.241***	−0.544***	0.000
	(0.306)	(0.114)	(0.005)
Observations	958,574	660,950	1,059,717
Adjusted R^2	0.765	0.838	0.682
Industry × Cohort Year FE	YES	YES	YES
Bank FE	YES	YES	YES
Borrower FE	YES	YES	YES
Loan Type FE	YES	YES	YES

Table A.17: Stacked Loan Default: Opaque Industry Analysis

Loan-year-panel stacked regression estimating the determinants of borrower default rates on bank type and loan characteristics during periods of industry run-ups in the stock market. The full sample covers the years 1996-2019. *Specialized Bank* is an indicator variable that is equal to 1 if the bank's five-year lending concentration in a single industry is at least 20%, the top-quartile cutoff of the pooled bank–year distribution, and 0 otherwise. *Runup* is an indicator variable that is equal to 1 equal-weighted industry excess return during the three years before the loan is originated is greater than or equal to 20% and 0 otherwise. Default is an indicator variable that is equal to 1 if the borrower's S&P credit rating is Default or Selective Default in year t and the loan is still outstanding in that year and 0 otherwise. Industries are identified using the two-digit SIC code. *Low Rating Coverage* is an indicator variable that equals to 1 if, in a given year, an industry falls below the cross-sectional median of credit rating coverage. Controls include borrower, loan, and lender controls. Borrower controls include credit rating indicator variables, size, book leverage, profitability, age, and book equity. Loan controls include loan type and the number of syndicate participants. Bank controls include size and tier 1 capital ratio. All variable definitions can be found in Table A.1 in the appendix. Standard errors are double clustered by bank and the cohort are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5% and 10%, respectively.

	(1) Default
Specialized Bank	−0.058
	(0.357)
Specialized Bank × Runup	−2.403*
	(1.272)
Specialized Bank × Low Rating Coverage	1.115**
	(0.546)
Specialized Bank × Runup × Low Rating Coverage	2.149**
	(0.920)
Bank Size	0.237
	(0.363)
Tier 1 Capital	−0.046
	(0.068)
Borrower Leverage	0.031**
	(0.012)
Borrower Profitability	−0.024
	(0.032)
Borrower Size	0.712*
	(0.371)
Borrower Credit Rating	1.504***
	(0.343)
Syndicate Size	−0.002
	(0.004)
Observations	5,546,774
Adjusted R^2	0.538
Industry × Cohort Year FE	YES
Industry × Year FE	YES
Bank FE	YES
Borrower FE	YES
Loan Type FE	YES