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 such runups typically precede weaker industry performance. 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 edge in their preferred sectors. The argument runs that repeated screening, monitoring, and lending to firms in the same industry build 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 default rates on average within their core industries (Blickle et al., 2023, 2024; 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 sharp 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 does the opposite of what an informationally advantaged lender should do. It expands lending and reduces its loan loss provisions, even though such runups are followed, on average, by weaker industry performance. Specialized banks do not tighten loan terms during runups: they do not raise spreads, demand more collateral, or shrink loan sizes. The loans they originate during runups in their preferred industry 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 are thought to enjoy thus

appears to break down, and indeed to invert, around episodes of strong industry-level returns.

This pattern is puzzling because industry runups are, on average, followed by deterioration in industry fundamentals. I show that the runups in my sample are associated with subsequent declines in industry profitability and equity returns, and with a contraction in industry debt growth, in the years that follow. Yet specialized banks, the lenders most invested in those industries, lean in. The fact that they do so without compensating through tighter contract terms or higher provisioning indicates that the elevated default rates are driven by the selection of borrowers rather than by mechanical changes in pricing. The pattern is also specific to specialized banks' preferred industries: their lending elsewhere shows no analogous behavior.

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 observes only its own industry's signal; a diversified bank observes signals from multiple industries. Both banks share the same degree of diagnostic overreaction. The asymmetry comes from their information sets. When one industry experiences a runup but other industries are quiet, the diversified bank uses the flat cross-industry signal as an anchor: inferring that the common factor is unlikely to be large, it attributes part of the positive own-industry signal to idiosyncratic noise rather than a fundamental improvement. The specialized bank, lacking this anchor, treats the entire signal as evidence of a genuine fundamental improvement and overreacts more strongly. 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 when own-industry signals are noisier (so that the cross-industry anchor is more informative).

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 precisely 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 account for the patterns. Industry capture, the idea that specialized banks extract rents from captive borrowers, does not explain the results: while capture is itself associated with higher default rates, controlling for it leaves the specialization-runup interaction essentially intact. Geographic clustering and prior lending relationships, both of which could in principle generate borrower-specific knowledge that travels with industry concentration, similarly leave the core effect unchanged. 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 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 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 those runups are followed, on average, by industry deterioration. 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.

[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).

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 default rates (Blickle et al., 2023). Other work finds that diversification reduces risk exposure (Tabak et al., 2011), or that diversification 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. (2023), 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 precisely because runup periods, during which I argue

it overextends, are relatively rare in any given sample. Consistent with this, Blickle et al. (2023) 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. (2023) 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 at lower spreads, and lend more readily to opaque borrowers, proxied by smaller firm size. While Blickle et al. (2023) 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 operates.

[2]My replication of Blickle et al. (2023) is necessarily partial. Their analysis relies on the FR Y-14Q supervisory 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 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 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]

[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.

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

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). 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 must have equity price data available from CRSP, which is used to construct industry-level stock return measures. Borrowers in financials (SIC 6000–6999), utilities (SIC 4910–4939), and miscellaneous industries (SIC 9900–9999) are excluded. Unless otherwise noted, the unit of observation is the bank–borrower–facility level. 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 Bank Specialization

Bank specialization is measured in a similar fashion to Blickle et al. (2023). While Blickle et al. (2023) 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 originations, 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:

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

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*, equal to one if a bank's specialization measure lies in the top quartile of the bank-year distribution, and zero otherwise. In my sample, the top-quartile cutoff corresponds to a specialization share of approximately 20%, so the indicator equivalently flags banks whose concentration in a single industry is 20% or greater.

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.

3.3 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). 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.

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. A runup is defined as an industry-year in which the three-year cumulative excess return is greater than or equal to 20%. 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 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 approximately 25% of bank-year observations as specialized. Within any given year, specialized banks often account for a larger share of the banks observed, as shown in Table A.2, reflecting their greater count in the sample relative to larger lenders. Specialized banks originate approximately 24% of loans in the sample. This share is close to their bank-year share because specialized banks tend to be smaller and originate fewer loans per bank than their nonspecialized peers. 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: on average they are followed by reversals in industry profitability, equity returns, and debt growth. I then document that, despite this subsequent deterioration, specialized banks expand their lending and reduce their loan loss provisions during runups in their preferred industry. At the loan level, specialized banks originate loans that 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 genuine improvements in industry fundamentals or whether they are followed by reversals. 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:

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

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-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 period $k \in \{-3, -2, -1\}$ captures dynamics during the buildup itself, while $k \in \{0, +1, +2\}$ traces post-runup outcomes.

The coefficients β_k reveal the evolution of industry outcomes before, during, and after runup episodes. The full specification is reported in Table A.4. Figures 3, 4, and 5 show that

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

runups coincide with sharp contemporaneous increases in profitability, equity valuations, and debt growth. However, these improvements are generally followed by reversals in subsequent years. The post-runup decline in profitability and stock returns, together with elevated debt growth during the expansion phase, 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., 2021) and at the industry level (Fahlenbrach et al., 2018).

These patterns indicate that runups are not merely permanent improvements in industry fundamentals but are instead followed by measurable deterioration. This reversal is central to the interpretation of the bank-level results that follow: if runups are followed by weaker performance, then sustained credit expansion and muted provisioning during the runup imply exposure to subsequent downside risk.

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 the lending behavior of specialized and nonspecialized banks before, during, and after runup episodes in their preferred industry.

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

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

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 $\text{Specialized Bank}_{b,t}$ indicator then captures whether that concentration exceeds the top quartile of the sample distribution. This ensures that nonspecialized banks

serve as a valid control group: they experience runups in their own top industry, but without the concentrated portfolio exposure that drives the differential belief distortions documented among specialized lenders. Second, because specialization is calculated from lagged lending (the five-year lookback), the Specialized $\text{Bank}_{b,t}$ indicator is predetermined with respect to runups and contemporaneous loan originations. Third, the coefficients δ_k are interpreted as the differential change in the loan ratio for specialized banks relative to nonspecialized banks in event year k, controlling for bank fixed effects and common time shocks; in words, they capture whether specialized banks expand (or contract) lending differently around runups than other banks.

The definition of $\text{Runup}_{b,k,t}$ for nonspecialized banks warrants additional discussion. By assigning each bank a single preferred industry, the industry with the highest lending share over the preceding five years, the design ensures a clean one-to-one match between banks and runup episodes, so that each bank contributes at most one runup observation per year. This avoids double-counting and keeps the event-study structure symmetric across bank types.

The cost of this approach is that, for nonspecialized 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 assigned only one of them as its "preferred" industry, even though its exposure to the other two is nearly identical. If a runup occurs in the second-ranked industry rather than the first, that bank is treated as a non-event observation, potentially introducing noise into the control group.

An alternative would be to define $\text{Runup}_{b,k,t}$ for nonspecialized banks as an indicator equal to one if *any* industry in which the bank holds positive exposure experiences a runup. This would increase statistical power and reduce the chance of misclassifying a bank as

unexposed when it has meaningful investment in a runup industry. However, this approach introduces its own complications. In particular, it would generate multiple runup episodes per bank in a given year whenever more than one of the bank's industries is simultaneously in a runup, complicating the event-study structure and the interpretation of the coefficients. More importantly, it would create an asymmetry relative to specialized banks, whose runup exposure is by construction tied to a single focal industry. This asymmetry could bias the interaction coefficients if nonspecialized banks' aggregate exposure to runup industries differs systematically from their top-industry exposure alone. Taken together, the top-industry definition is the more conservative and internally consistent choice. It understates nonspecialized banks' aggregate runup exposure, which if anything biases against finding a differential effect for specialized banks.

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 $k = -4$, specialized banks increase their relative C&I exposure during the runup years and revert toward the baseline in the years following the runup. This is striking given the evidence in Section 4.1 that runups are followed by industry-level reversals: specialized banks lend most aggressively into industries that subsequently weaken.

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 $k = -4$, specialized banks reduce provisions during the runup years and revert toward the baseline only after the runup has concluded; they do not raise provisions

contemporaneously with the runup. Combining the two outcomes, specialized banks behave as though runups represent good news for credit risk, expanding exposure and reducing provisioning even as the industry-level evidence in Section 4.1 shows the opposite.

4.3 Loan-Level Default Risk

The bank-level evidence shows that specialized banks expand exposure and reduce provisioning during runups. A natural follow-up question is whether the loans they originate in this window 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.

Following Murfin and Njoroge (2015), *Default* is defined as an indicator equal to one if the borrower's S&P credit rating reaches "Default" or "Selective Default" at any point during the life of the loan. 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 subsequent time-varying industry shocks. 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 during runups are associated with differential ex post default risk relative to loans extended by nonspecialized banks to the same industry at the same time. Standard errors are clustered at the bank level.

Table 2 shows that loans issued by specialized banks to their preferred industries during runups exhibit an ex post default rate that is 0.621 percentage points higher than that of comparable loans issued by nonspecialized banks. Given a sample mean 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 lean into their preferred industries during runups, 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 during runups 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 during runups, and there is no significant effect on collateralization. Taken together, the evidence does not support the interpretation that specialized banks anticipate elevated risk and price it into contract terms at origination. The elevated default rates documented above appear to be driven primarily by the selection margin, the types of borrowers funded during runups, rather than by systematic adjustments in contract structure.

The patterns in this section are difficult to reconcile with the standard interpretation of bank specialization as a source of superior information. Industry runups are followed, on average, by reversals in industry profitability, equity returns, and debt growth (Section 4.1); yet specialized banks lean into their preferred industries during runups, expanding lending and reducing provisioning (Section 4.2); the loans they originate in those windows 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 that is followed, on average, by industry deterioration. The next section proposes an explanation for this pattern that takes both the average informational advantage and the cyclical reversal seriously.

5 A Diagnostic Expectations Explanation

The patterns documented in Section 4 are puzzling under a fully rational informational view of bank specialization: specialized banks, who are supposed to know their industries best, originate the loans that are most likely to default and offer them on looser terms in the very industries whose signals later weaken. In this section I propose an explanation for these facts that retains the standard informational asymmetry between specialized and diversified banks but allows both bank types to update their beliefs in a behaviorally biased way. The model is in the spirit of the diagnostic expectations framework of Bordalo et al. (2018, 2020).

The substantive economics is simple. Banks differ in the degree to which they specialize

in lending to particular industries. Specialized banks, those that concentrate a large share of their loan portfolio in a single industry, are often viewed as better informed about that industry's fundamentals (Blickle et al., 2023, 2024). Such informational advantages may arise from more intensive monitoring, longer lending relationships, or superior access to industry-specific information. This intuition underlies a large literature on relationship lending and bank specialization (e.g., Sharpe 1990; Petersen and Rajan 1994; Shim 2019; Blickle et al. 2023; Blickle et al. 2024).

At the same time, recent work shows that agents may over-extrapolate from favorable signals when forming expectations about future fundamentals (Bordalo et al., 2018, 2020, 2021; Maxted, 2024). In these models, agents overweight signals that appear especially representative of future states of the world, generating overoptimism following positive news. Building on the diagnostic expectations framework of Bordalo et al. (2020), I examine how bank specialization interacts with belief distortions. Both specialized and diversified banks share the same degree of diagnostic overreaction, but they observe different sets of signals. This asymmetry in information sets, rather than any difference in the severity of the bias itself, generates heterogeneous overreaction during industry-specific runups.

In the setting below, a specialized bank observes only its own industry's signal, while a diversified bank additionally observes signals from other industries. During an industry-specific runup, the diversified bank uses the flat cross-industry signal as an anchor, inferring that the common factor is unlikely to be large and attributing part of the positive own-industry signal to idiosyncratic noise. The specialized bank, lacking this anchor, treats the entire positive signal as evidence of a genuine fundamental improvement and overreacts more strongly. While the model has a number of empirical implications, I focus on two that I take

to the data in Section 6: (i) specialized banks should hold systematically more optimistic beliefs about their preferred industries during runups, and (ii) the differential should be larger when the cross-industry anchor is more informative, that is, in industries where own-industry signals are noisier.

5.1 Setup

There are two industries $i \in \{1, 2\}$. Industry 1 experiences a runup and is the industry of empirical interest. Industry fundamentals follow AR(1) processes:

$$x_{i,t} = \rho\, x_{i,t-1} + \varepsilon_{i,t}, \qquad |\rho| < 1. \tag{6}$$

Correlated fundamentals. The innovation vector $(\varepsilon_{1,t}, \varepsilon_{2,t})$ has a factor structure:

$$\varepsilon_{i,t} = \varepsilon^{c}_{t} + \varepsilon^{id}_{i,t}, \tag{7}$$

where $\varepsilon^{c}_{t} \sim \mathcal{N}(0, \sigma^2_c)$ is a common shock shared across industries and $\varepsilon^{id}_{i,t} \sim \mathcal{N}(0, \sigma^2_{id})$ is idiosyncratic, with all components mutually independent. This gives:

$$\mathrm{Var}(\varepsilon_{i,t}) = \sigma^2_\varepsilon \equiv \sigma^2_c + \sigma^2_{id}, \qquad \mathrm{Cov}(\varepsilon_{1,t},\, \varepsilon_{2,t}) = \sigma^2_c > 0. \tag{8}$$

The covariance $\sigma^2_c > 0$ is the key parameter: it is what makes the industry-2 signal informative about $x_{1,t}$. When $\sigma^2_c = 0$ the industries are independent and the industry signals are not informative of other industry fundamentals; when $\sigma^2_c \to \sigma^2_\varepsilon$ both industries move together

and the diversified bank gains maximum information from $s_{2,t}$.

Signals. Each industry generates a noisy signal:

$$s_{i,t} = x_{i,t} + \eta_{i,t}, \qquad \eta_{i,t} \sim \mathcal{N}(0, \sigma_\eta^2), \quad \text{independent across } i \text{ and } t. \tag{9}$$

Banks. Two banks differ in which signals they observe:

- **Specialized bank** S: lends only to industry 1. Observes $s_{1,t}$ only.
- **Diversified bank** D: lends to both industries. Observes both $s_{1,t}$ and $s_{2,t}$.

I take specialization as exogenously given. The key assumption is that a bank's information set is shaped by its lending portfolio: industry signals are generated through the lending relationship itself, via loan screening, borrower monitoring, and the accumulation of industry-specific expertise that comes from repeated engagement with firms in a sector. A bank that does not lend to industry 2 therefore does not participate in these information-generating activities and cannot condition on $s_{2,t}$ when forming beliefs about $x_{1,t}$. This is consistent with the broader relationship lending literature, which emphasizes that proprietary information is produced as a byproduct of the lending relationship and is not freely available to outside lenders (Sharpe, 1990; Petersen and Rajan, 1994).

5.2 Rational Updating

Specialized bank. With only $s_{1,t}$, the posterior mean for $x_{1,t}$ follows the standard univariate Kalman filter:

$$\mu_{1,t}^{S,B} = \rho \mu_{1,t-1} + K_1 \, \Delta s_{1,t}, \tag{10}$$

where $\Delta s_{i,t} \equiv s_{i,t} - \rho\mu_{i,t-1}$ is the signal innovation for industry i, and $K_1 = p\,/\,(p + \sigma_\eta^2)$ is the univariate Kalman gain with $p \equiv \sigma_\varepsilon^2$ denoting the prior variance of $x_{i,t}$.

Diversified bank. With both signals, the posterior mean for $x_{1,t}$ follows the multivariate Kalman filter. Let

$$\mathbf{P} = \begin{pmatrix} p & c \\ c & p \end{pmatrix}, \qquad \mathbf{R} = \sigma_\eta^2\,\mathbf{I}_2 \tag{11}$$

be the prior covariance matrix of $(x_{1,t}, x_{2,t})$ with $c \equiv \sigma_c^2$. The multivariate Kalman gain matrix is:

$$\mathbf{K} = \mathbf{P}(\mathbf{P} + \mathbf{R})^{-1}. \tag{12}$$

Setting $\alpha \equiv p + \sigma_\eta^2$, the relevant elements of $\mathbf{K}$ for beliefs about $x_{1,t}$ are:

$$K_{11} = \frac{p\alpha - c^2}{\alpha^2 - c^2}, \qquad K_{12} = \frac{c\,\sigma_\eta^2}{\alpha^2 - c^2}, \tag{13}$$

where K_{11} is the weight on the own-industry signal $s_{1,t}$ and $K_{12} > 0$ is the weight on the cross-industry signal $s_{2,t}$. The rational posterior mean for industry 1 is:

$$\mu_{1,t}^{D,B} = \rho\mu_{1,t-1} + K_{11}\,\Delta s_{1,t} + K_{12}\,\Delta s_{2,t}. \tag{14}$$

Own-signal weight comparison. A simple calculation verifies that $K_1 > K_{11}$:

$$K_1 - K_{11} = \frac{c^2\,\sigma_\eta^2}{\alpha(\alpha^2 - c^2)} > 0. \tag{15}$$

The diversified bank places less weight on $s_{1,t}$ than the specialized bank because part

of the information in $s_{1,t}$ about the common component ε_t^c is already captured by $s_{2,t}$. Correspondingly, the diversified bank extracts additional information through $K_{12}\,\Delta s_{2,t}$.

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 $\theta > 0$. The diagnostic posterior mean for $x_{1,t}$ is formed by applying this distortion to each innovation entering the update.

Specialized bank:

$$\mu_{1,t}^{S} = \rho\mu_{1,t-1} + (1+\theta)\,K_1\,\Delta s_{1,t}. \tag{16}$$

Diversified bank:

$$\mu_{1,t}^{D} = \rho\mu_{1,t-1} + (1+\theta)\,K_{11}\,\Delta s_{1,t} + (1+\theta)\,K_{12}\,\Delta s_{2,t}. \tag{17}$$

The diagnostic overreaction in each bank's beliefs about industry 1 is:

$$\Omega_t^{S} \equiv \mu_{1,t}^{S} - \mu_{1,t}^{S,B} = \theta\,K_1\,\Delta s_{1,t}, \tag{18}$$

$$\Omega_t^{D} \equiv \mu_{1,t}^{D} - \mu_{1,t}^{D,B} = \theta(K_{11}\,\Delta s_{1,t} + K_{12}\,\Delta s_{2,t})\,. \tag{19}$$

5.4 Relative Overreaction

The difference in overreaction between the two banks, evaluated at their beliefs about industry 1, is:

$$\begin{aligned}\Omega_t^S - \Omega_t^D &= \theta\, K_1\, \Delta s_{1,t} - \theta(K_{11}\, \Delta s_{1,t} + K_{12}\, \Delta s_{2,t}) \\ &= \theta[(K_1 - K_{11})\, \Delta s_{1,t} - K_{12}\, \Delta s_{2,t}]\,. \end{aligned} \tag{20}$$

Substituting the explicit expressions for $K_1 - K_{11}$ and K_{12}:

$$\Omega_t^S - \Omega_t^D = \frac{\theta\, c\, \sigma_\eta^2}{\alpha^2 - c^2}\left[\frac{c}{\alpha}\, \Delta s_{1,t} - \Delta s_{2,t}\right]. \tag{21}$$

This expression is the central result of the model. It shows that relative overreaction about industry 1 depends entirely on the gap between the weighted own signal and the cross-industry signal, scaled by the cross-industry covariance c and the distortion parameter θ.

Implications

PROPOSITION 1 (Industry Runup)**.** *Suppose industry 1 is in a runup:* $\Delta s_{1,t} > 0$ *and* $\Delta s_{2,t} = 0$*. Then* $\Omega_t^S > \Omega_t^D > 0$*.*

When only industry 1 receives a positive signal, the cross-industry term $K_{12}\, \Delta s_{2,t}$ is zero. The specialized bank's overreaction is $\theta K_1\, \Delta s_{1,t}$, while the diversified bank's overreaction is the smaller $\theta K_{11}\, \Delta s_{1,t}$, since it has already absorbed some of the information in $s_{1,t}$ through the cross-industry channel and has no positive $s_{2,t}$ to further inflate beliefs. Both banks overreact, but the specialized bank does so more.

The diversified bank infers from $\Delta s_{2,t} \approx 0$ that the common factor ε_t^c is unlikely to be large. It therefore attributes part of the positive $\Delta s_{1,t}$ to idiosyncratic industry-1 noise rather than a broad fundamental improvement. The specialized bank, receiving no such anchor, treats the entire positive signal as evidence of a genuine improvement.

PROPOSITION 2 (Own-Signal Noise)**.** *Suppose industry 1 is in a runup:* $\Delta s_{1,t} > 0$ *and* $\Delta s_{2,t} = 0$*. Then the differential overreaction simplifies to*

$$\Omega_t^S - \Omega_t^D = \frac{\theta\, c^2\, \sigma_\eta^2}{\alpha\,(\alpha^2 - c^2)}\, \Delta s_{1,t}, \tag{22}$$

which is increasing in σ_η^2 *for* σ_η^2*.*

The right-hand side of (22) carries σ_η^2 in the numerator: when own-industry signals are very precise ($\sigma_\eta^2 \to 0$), both banks rely almost entirely on $s_{1,t}$ and the wedge in their updating closes. As own-industry signals become noisier, the diversified bank's cross-Kalman weight $K_{12} = c\sigma_\eta^2/(\alpha^2 - c^2)$ rises in absolute terms and relative to its own-signal weight K_{11}. The diversified bank therefore puts greater weight on the flat industry-2 signal and revises its posterior on $x_{1,t}$ down toward the prior. The specialized bank, who cannot observe $s_{2,t}$, has no comparable anchor and overreacts at the full diagnostic rate. The wedge $\Omega_t^S - \Omega_t^D$ is consequently largest in industries where own-industry fundamentals are hard to evaluate, generating the second empirical implication that I take to the data in Section 6.2.

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 diversified bank's advantage during a runup comes from using the cross-industry signal as an anchor, the differential overreaction by specialized banks should be larger when own-industry signals are noisier, that is, in industries where credit-relevant fundamentals are harder to evaluate. 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 × year × 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 × year × 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:

$$\begin{aligned}\text{Sentiment}_{b,i,t,c} = \gamma\Big(&\text{Specialized Bank}_b \times \text{Treated}_{i,c}\Big) \\ &+ \sum_{k \neq -4} \delta_k \Big(\text{Specialized Bank}_b \times \text{Treated}_{i,c} \times \mathbf{1}[k_{t,c} = k]\Big) \\ &+ \alpha_b + \mu_{i,t,c} + \varepsilon_{b,i,t,c}, \end{aligned} \tag{23}$$

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, $p \approx 0.014$), 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, $p \approx 0.028$), 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 when own-industry signals are noisier. Intuitively, the diversified bank's advantage during a runup is the ability to anchor its update on the cross-industry signal; that anchor matters more when the own-industry signal is itself less informative. I exploit cross-industry variation in valuation opacity to test this implication. I construct *Low 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 Coverage*, *Specialized Bank*, and *Runup*.

The triple-interaction coefficient is positive and economically large (Table 4). The increase in default risk associated with specialization during runups 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 during runups. These patterns line up with the model: the differential is larger precisely where the cross-industry anchor matters most, and is not absorbed by compensating contractual adjustments. 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. 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. The triple interaction *Specialized Bank* $\times$ *Runup* $\times$ *Industry Capture* on the default outcome is -0.839 with a standard error of 1.526, and is not statistically distinguishable from zero. The *Specialized Bank* $\times$ *Runup* coefficient remains positive and statistically significant, with a point estimate of 1.021, economically similar to the baseline estimate of 0.621. Industry capture cannot account for the elevated default rates of specialized banks during runups: the differential is not concentrated in industries where the bank holds a dominant market position.

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. The triple interaction with *Relationship* on the default outcome is 0.287, and the triple interaction with *State* is -0.374. Neither is statistically distinguishable from zero. The *Specialized Bank* $\times$ *Runup* coefficient remains positive and statistically significant in both specifications, with point estimates of 0.603 and 0.607, economically similar to the baseline of 0.621. Neither geographic

co-location nor prior lending relationships absorb the differential default risk of specialized banks during runups: the effect is not concentrated in loans to nearby borrowers or to past borrowers.

To further examine whether the elevated default rates of specialized banks during runups 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 during runups are entirely attributable to 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 are not absorbed by industry capture, geographic co-location, or borrower-specific relationship lending, 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 and Njoroge (2015) 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). The results are qualitatively and quantitatively consistent with those from the baseline specification.

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. (2023), which benchmarks a bank's allocation to an industry against that industry's share of aggregate syndicated lending:

$$\text{Excess Specialization}_{b,i,t} = \frac{\text{LoanAmount}_{b,i,t}}{\sum_i \text{LoanAmount}_{b,i,t}} - \frac{\text{LoanAmount}_{i,t}}{\sum_i \text{LoanAmount}_{i,t}}. \tag{24}$$

The first term is the fraction of bank b's syndicated lending directed to industry i in period t, and the second is industry i's share of all syndicated lending in that period, so that only allocations above the market-wide norm register as specialization. For instance, a bank that channels 15% of its syndicated lending to the oil and gas industry in a period when 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%. Because the measure is constructed as a difference rather than a ratio, it avoids the extreme values that a relative, ratio-based measure produces when a bank concentrates in an industry that receives little aggregate lending. I retain the baseline definition of *Specialized Bank*: exactly as in the main specification, the indicator equals one when a bank lies in the top quartile of the excess specialization distribution and zero otherwise. 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. Across all of these specifications, results remain qualitatively and quantitatively consistent with the main findings. 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 contract terms.

9 Conclusion

Industry stock-market runups are followed, on average, by deterioration in industry profitability, equity returns, and debt growth, 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 lending and reduce loan-loss provisions during runups in their preferred industries, and the loans they originate during these windows 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: specialized banks lack the cross-industry signals that allow diversified banks to anchor their updates during industry-specific runups, and so overreact more strongly to favorable own-industry news. 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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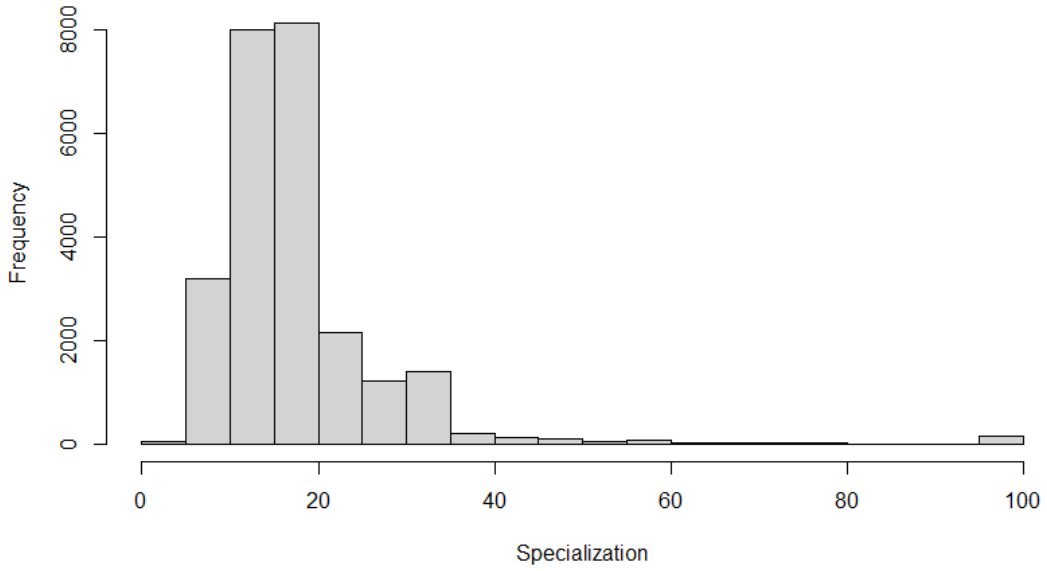


Figure 1. Distribution of Specialization

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

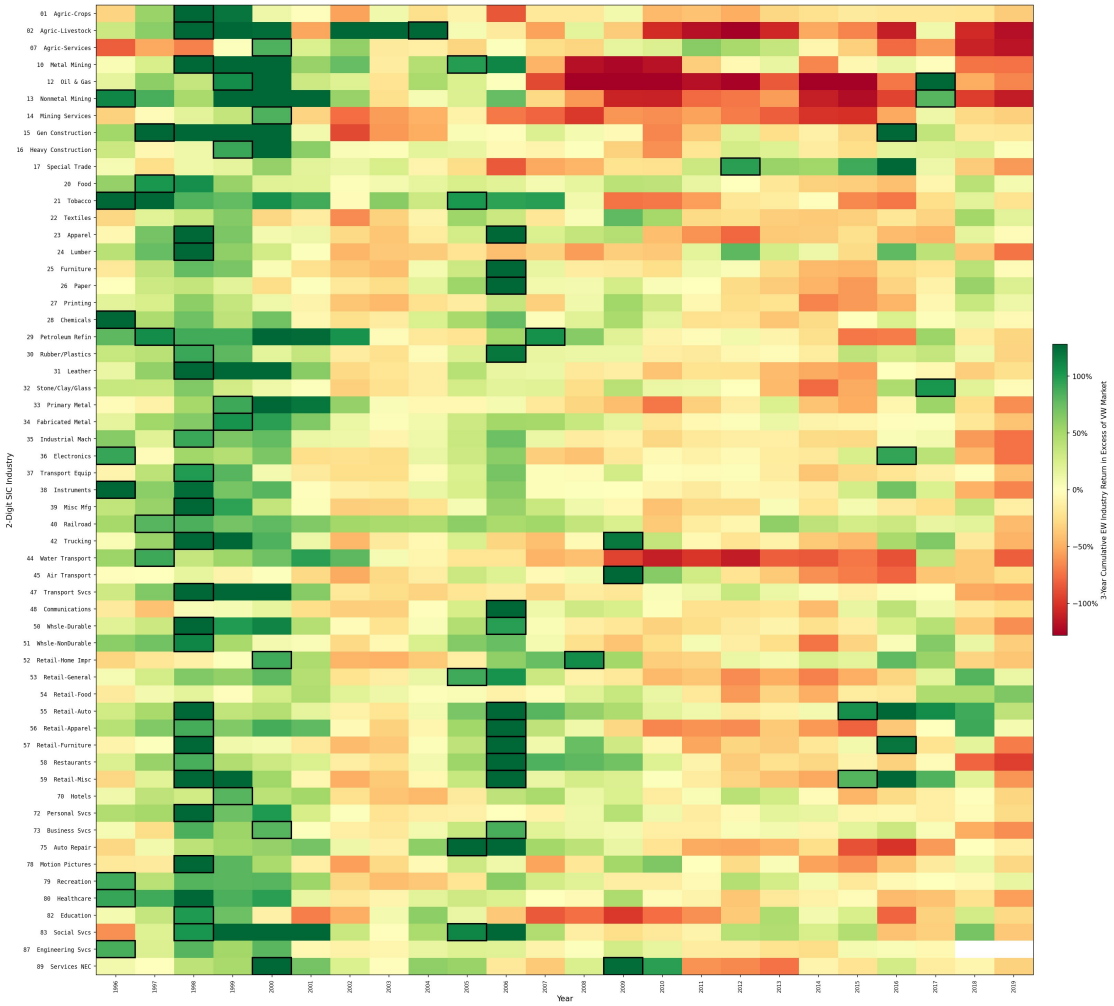


Figure 2. Industry Runup Classification

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 risk-weighted assets to the book value of total 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

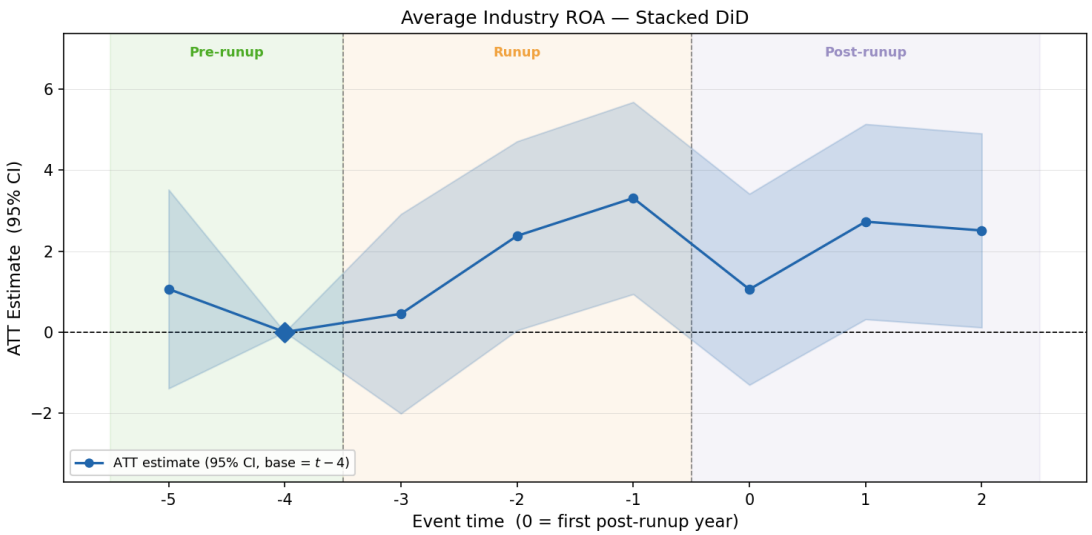


Figure 3. Industry ROA

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.

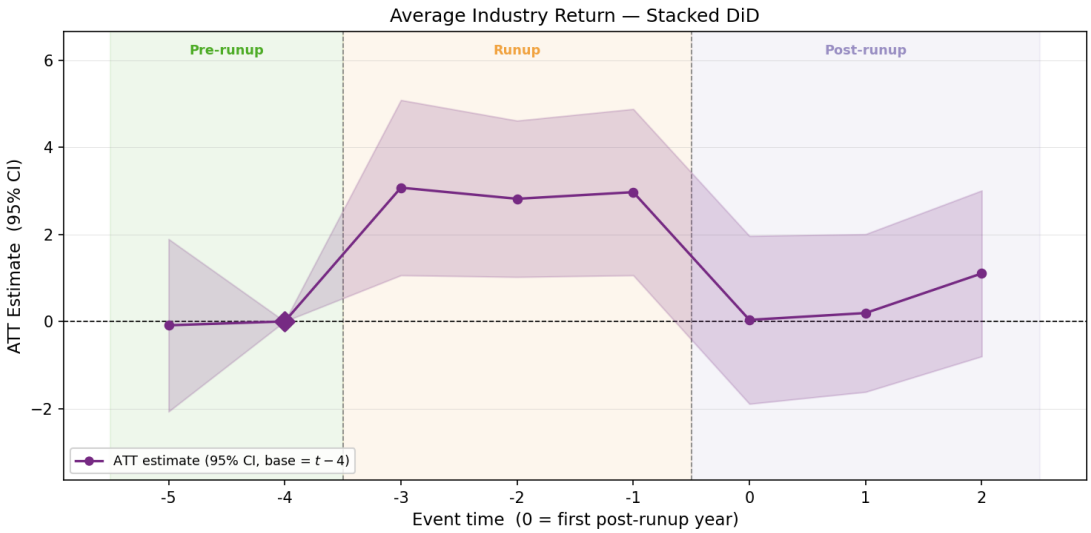


Figure 4. Industry Return

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.

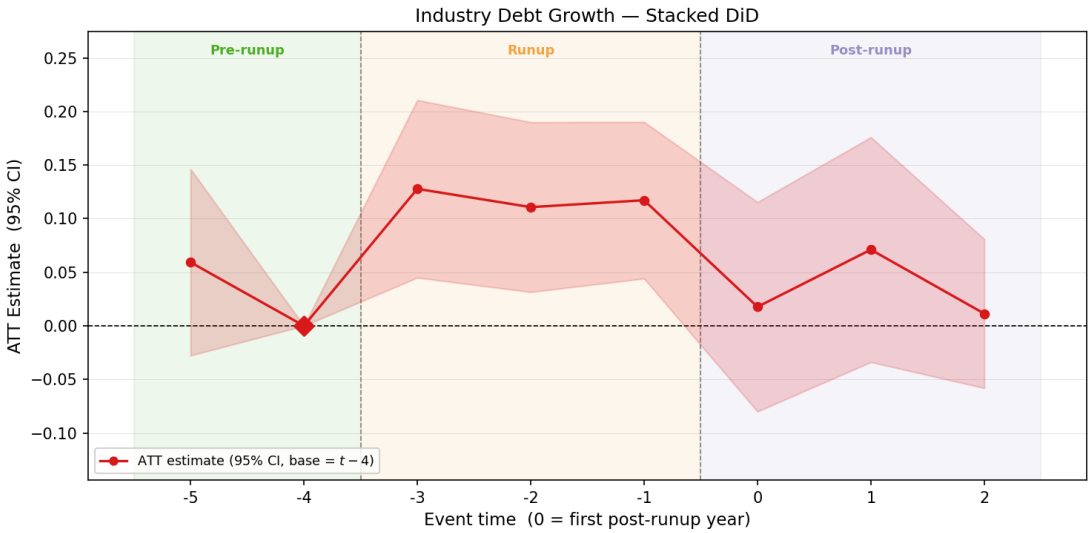


Figure 5. Industry Debt Growth

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.

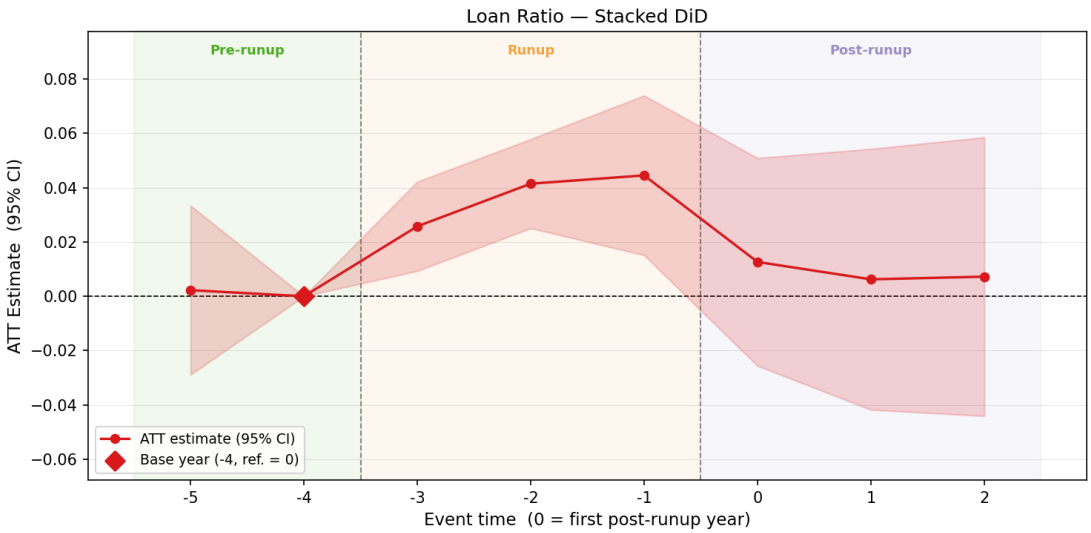


Figure 6. Bank Loan Ratio

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. Each coefficient reflects the average treatment effect on the treated (ATT) for specialized banks relative 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.

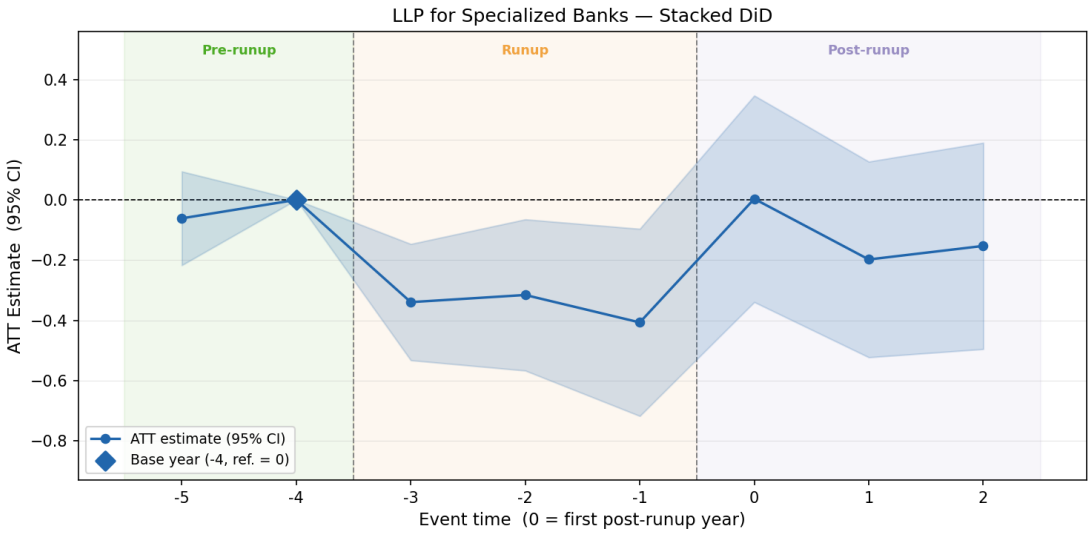


Figure 7. Bank Loan Loss Provisions

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. Each coefficient reflects the average treatment effect on the treated (ATT) for specialized banks relative 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 × bank and cohort × year. Standard errors are clustered at the bank level.

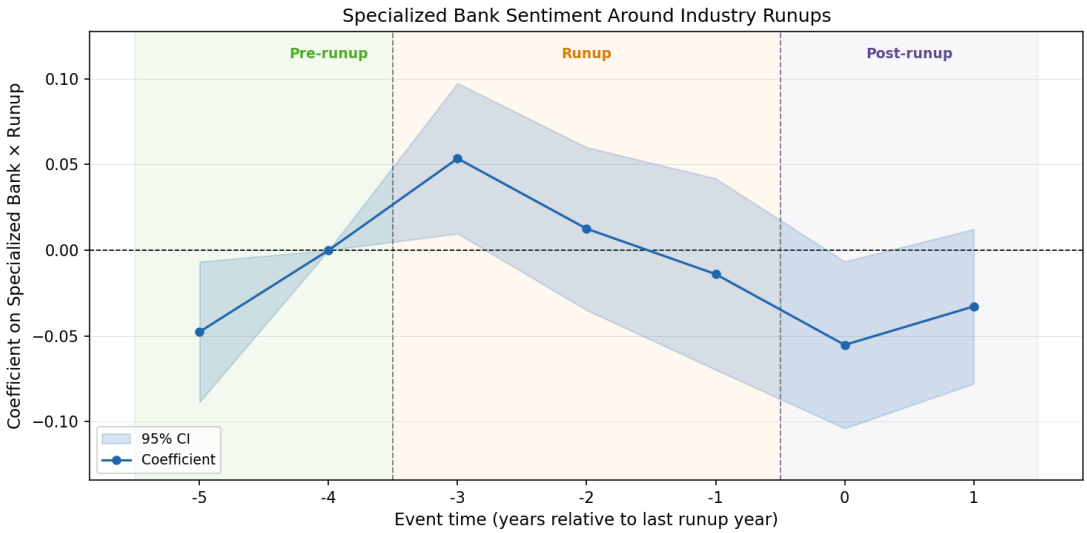


Figure 8. Sentiment

The figure plots the coefficients δ_k from the stacked event-study regression in Equation (23), 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 × industry × 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 is in the top quartile of specialization 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. *Default* is an indicator variable that is equal to 1 if the borrower's S&P credit rating is ever Default or Selective Default during the life of the loan 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	-0.163	-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-squared	0.409	0.302	0.280	0.269	0.247
Industry X Year FE	YES	NO	YES	YES	NO
Industry X 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 is in the top quartile of specialization 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	-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-squared	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 is in the top quartile of specialization 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. *Default* is an indicator variable that is equal to 1 if the borrower's S&P credit rating is ever Default or Selective Default during the life of the loan and 0 otherwise. Industries are identified using the two-digit SIC code. *Low 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 Coverage	0.491
	(0.311)
Specialized Bank × Runup × Low 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 × Cohort 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 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 has at least 20% of their loan portfolio concentrated in a single industry over the previous five years 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 ever Default of Selective Default during the life of the loan and 0 otherwise. Industries are identified using the two-digit SIC code. *Low 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 Coverage	0.044	4.294	0.123
	(0.108)	(4.849)	(0.102)
Specialized Bank × Runup × Low 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 is in the top quartile of specialization 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. *Default* is an indicator variable that is equal to 1 if the borrower's S&P credit rating is ever Default or Selective Default during the life of the loan 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	0.318	0.319	0.315
Controls	YES	YES	YES
Industry × Cohort 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 is in the top quartile of specialization 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. *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)		
Spec. 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)		
Spec. 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)	
Spec. 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)	
Spec. 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)
Spec. 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)
Spec. 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 4.1, 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, in percentage points (alldrawn).	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 firm, in a given year, falls below the cross-sectional median of firm size and 0 otherwise.	CRSP
Low Profit	An indicator variable that is 1 if the firm, in a given year, falls below the cross-sectional median of industry profitability and 0 otherwise.	CRSP
Low Coverage	An indicator variable that is 1 if the firm, in a given year, falls below the cross-sectional median of the fraction of firms with a credit rating and 0 otherwise.	Compustat
Default	An indicator variable that is 1 if the S&P rates the borrower firm as Default (D) or Selective Default (SD) during the lifetime of the loan and 0 otherwise.	Compustat
Ln(Amount)	The natural logarithm of the loan amount provided by the bank.	DealScan
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. Column (1) reports the total number of unique banks per year. Column (2) reports the number of specialized banks per year. Column (3) reports the total number of loans per year. Column (4) reports the number of loans made by specialized banks to their preferred (focal) industry. Column (5) reports the number of loans made by nonspecialized banks to their top industry. Column (6) reports the number of loans made by nonspecialized banks to industries other than their top industry. Columns (4), (5), and (6) do not sum to column (3) because loans made by specialized banks outside their preferred industry are not separately reported.

Year	(1) Total Banks	(2) Specialized Banks	(3) Total Loans	(4) Spec Loans Focal Ind.	(5) Nonspec Loans Focal Ind.	(6) Nonspec Loans Non-Focal Ind.
1996	31	16	502	104	42	320
1997	36	20	672	127	61	450
1998	37	23	661	178	56	372
1999	37	23	773	146	46	539
2000	38	24	925	145	66	669
2001	40	25	959	145	73	693
2002	41	24	946	154	80	672
2003	40	20	862	63	88	677
2004	39	19	957	63	84	776
2005	37	19	984	117	79	749
2006	38	18	943	151	75	667
2007	35	18	891	147	64	626
2008	30	16	478	63	35	352
2009	30	16	358	57	24	240
2010	34	20	653	78	53	494
2011	31	21	1042	261	65	663
2012	29	13	891	96	80	695
2013	31	21	1135	137	74	873
2014	30	18	1165	146	112	878
2015	33	17	1179	111	111	919
2016	30	13	1065	153	90	790
2017	30	18	1172	203	70	856
2018	30	16	1224	170	112	904
2019	33	23	1069	216	69	733

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 a bank allocates at least 20% of its loan portfolio to a single industry, measured over the previous five years. *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
$\text{Runup}_{t-5} \times$ Specialized Bank	-0.048^{**}
	(0.021)
$\text{Runup}_{t-4} \times$ Specialized Bank	0
	(ref.)
$\text{Runup}_{t-3} \times$ Specialized Bank	0.054^{**}
	(0.022)
$\text{Runup}_{t-2} \times$ Specialized Bank	0.013
	(0.024)
$\text{Runup}_{t-1} \times$ Specialized Bank	-0.014
	(0.028)
$\text{Runup}_{t} \times$ Specialized Bank	-0.055^{**}
	(0.025)
$\text{Runup}_{t+1} \times$ 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 × Industry FE	YES	YES	YES
Cohort × 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 is in the top quartile of specialization over the previous five years 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	205,559	14,813
Adjusted R^2	0.674	0.881
Cohort × Bank FE	YES	YES
Cohort × 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 has at least 20% 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 ever Default or Selective Default during the life of the loan 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 × Cohort 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 has at least 20% 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. *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 has 20% of their loan portfolio concentrated in a single industry 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. *Altman* is the Altman Z-score (Altman, 1968) of the borrowing firm at the time of origination. CHS 3 is the three-year predicted probability of default using the model and coefficients provided by Campbell et al. (2008) in percentage points 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 × Cohort 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 ever Default or Selective Default during the life of the loan 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 × Cohort 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 has at least 20% 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 15% and 0 otherwise. *Default* is an indicator variable that is equal to 1 if the borrower's S&P credit rating is ever Default or Selective Default during the life of the loan 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 × Cohort 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 has at least 20% 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 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. (2023), 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, $\frac{\text{LoanAmount}_{b,i,t}}{\sum_i \text{LoanAmount}_{b,i,t}} - \frac{\text{LoanAmount}_{i,t}}{\sum_i \text{LoanAmount}_{i,t}}$. 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 ever Default or Selective Default during the life of the loan 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-squared	0.410	0.303	0.280	0.270	0.248
Industry X Year FE	YES	NO	YES	YES	NO
Industry X 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. (2023), 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, $\frac{\text{LoanAmount}_{b,i,t}}{\sum_i \text{LoanAmount}_{b,i,t}} - \frac{\text{LoanAmount}_{i,t}}{\sum_i \text{LoanAmount}_{i,t}}$. 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-squared	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 has at least 20% 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 ever Default or Selective Default during the life of the loan 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 has at least 20% 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 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(amount)
Specialized Bank	−0.148***	−5.203*	0.136**
	(0.053)	(3.060)	(0.057)
Specialized Bank × Runup	−0.131	5.600	−0.100*
	(0.102)	(3.448)	(0.058)
Bank Size	−0.114	−3.479	0.104*
	(0.085)	(2.374)	(0.060)
Tier 1 Capital	0.009	−0.172	−0.020*
	(0.008)	(0.348)	(0.010)
Borrower Age	0.061	14.054***	0.113**
	(0.151)	(3.077)	(0.045)
Borrower Leverage	−0.002	0.030	0.004
	(0.004)	(0.133)	(0.003)
Borrower Profitability	−0.019***	−0.327***	−0.003
	(0.003)	(0.092)	(0.002)
Borrower Size	−0.103**	−5.154***	0.325***
	(0.044)	(1.207)	(0.034)
Borrower Credit Rating	0.012***	−0.043	0.010***
	(0.003)	(0.148)	(0.003)
Syndicate Size	−0.022***	−0.544***	0.000
	(0.003)	(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 has at least 20% of their loan portfolio concentrated in a single industry over the previous five years 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 SP credit rating is ever Default of Selective Default during the life of the loan and 0 otherwise. Industries are identified using the two-digit SIC code. *Low 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 Coverage	1.115**
	(0.546)
Specialized Bank × Runup × Low 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