Credit Ratings and Financial Vulnerability

Runxi Niu*
Department of Economics
Norwegian School of Economics

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Abstract

Credit ratings shape firms' financing conditions, yet they often diverge from fundamental default risk. Using Norwegian firm data, I show that fundamentals predict bankruptcy even within identical agency rating categories. Mapping out-of-sample default predictions onto the rating scale, I construct a fundamentals-based rating. Holding fundamentals-based risk constant, firms with higher agency ratings have lower borrowing costs and faster debt growth, especially among small businesses. In a heterogeneous-firm model where assessments shape borrowing and credit allocation, assessment-based pricing raises total debt only slightly but shifts credit toward higher-risk and smaller firms at a common wage and aggregate lending spread. In general equilibrium, imperfect assessments amplify investment contractions more following a bank-capital shock than a productivity shock. This gap stems mainly from how loans are priced after a shock. Favorable ratings can cushion firm financing during a productivity downturn, but offer less support when bank-capital losses raise lenders' required returns.

Keywords: Credit ratings; Credit allocation; Firm financing; Financial vulnerability; Firm heterogeneity.

*Email: runxi.niu@nhh.no

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1 Introduction

Credit expansions have historically preceded financial crises (Schularick and Taylor, 2012). Yet aggregate credit growth alone does not reveal which firms accumulate debt or how vulnerable their balance sheets become. This distinction matters because borrowers' balance sheets shape the amplification of aggregate shocks (Bernanke et al., 1999). One factor shaping these balance sheets is how lenders assess firms' creditworthiness. Favorable assessments can ease financing conditions and encourage borrowing, leaving firms with financial obligations that may persist beyond the initial assessment advantage. This paper asks whether credit assessments can create persistent financial vulnerability by changing the allocation of credit, even without a substantial expansion in aggregate borrowing.

The effect of more favorable credit assessments on future risk is unclear. Cheaper refinancing can help firms meet their debt obligations, but it may also allow them to carry debt they would otherwise have repaid. To study the dynamic consequences of these financing choices, I combine Norwegian firm-level evidence with a heterogeneous-firm model. Among firms with similar risk based on observable fundamentals, more favorable agency ratings are associated with lower borrowing costs and faster debt growth. In the model, lenders' assessments affect debt prices, and firms adjust their borrowing in response. These financing choices change the distribution of credit across risk states, increasing exposure to the same future adverse shock even after the initial assessment advantage fades. Changes in credit allocation account for a substantial share of the additional credit risk. The effect on aggregate investment depends on the source of the shock. While the firms responsible for most of the additional credit losses account for a small share of total investment, shocks that tighten bank lending conditions also affect low-risk firms that undertake a large share of investment.

The empirical analysis first asks whether firms' financial information contains default information not captured by agency ratings, which serve as an observable proxy for credit assessments. I match Dun & Bradstreet credit ratings to Norwegian firms' financial statements and bankruptcy records to construct a panel covering 2008 to 2017. Financial characteristics predict subsequent bankruptcy even after controlling for agency rating-by-year fixed effects. I summarize this risk information in a fundamentals-based rating. The prediction model excludes agency ratings to provide a benchmark based on financial information against which to compare agency assessments. Each year, training and calibration use only earlier observations. I then map the predicted probabilities to the agency rating scale using historical default rates by rating. The gap between the two ratings measures how favorable agency assessments are relative to risk based on observable fundamentals.

Among firms with similar fundamentals-based risk, more favorable agency ratings are associated with lower borrowing costs and faster debt growth. A one-notch higher agency rating corresponds to average borrowing costs about 60 basis points lower and a debt growth rate about 1 percentage point higher. The positive relationship with debt growth is concentrated among small firms. To study the dynamic consequences of these financing relationships, I use the model to track how different credit assessments shape the distribution of debt and capital, then compare the credit losses these distributions generate under the same future shock.

Firms in the model finance themselves with internal funds and long-term debt and jointly choose borrowing and investment. Their financing problem is closely related to those in Khan, Senga, and Thomas (2016) and Ottonello and Winberry (2020). To capture how credit assessments can deviate from true fundamentals, I introduce a persistent disturbance into lenders' forecasts of firm productivity. Firms base their decisions on the true productivity process. Assessment disturbances are independent of productivity innovations, allowing the model to isolate the effects of credit assessments through financing conditions. More favorable assessments improve lenders' expectations of future repayment and raise the price of a given debt contract. Firms can then raise more funds for the same face value of debt, making existing debt easier to refinance. As borrowing increases, firms may face higher default risk in the future. With long-term debt and gradual adjustment of debt and capital, past financing choices can continue to affect risk after the initial assessment advantage fades.

I calibrate the model using Norwegian firm data and compare its financing responses and credit distribution with those in the data. The average responses of borrowing costs and debt are close to the empirical estimates, and both the model and the data show stronger responses among small firms. The model understates the share of bank credit held by the largest firms, so I also compare risk allocation among the remaining firms. Once the largest 1% of firms are excluded, high-risk firms hold similar shares of bank credit in the model and the data.

I compare loan portfolios formed under different credit assessments by exposing them to the same future shock under common pricing conditions. This comparison measures the risk left by past financing choices. Relative to a counterfactual with fundamentals-based pricing, assessment-based pricing raises aggregate credit by about 0.9% in the long run and increases the credit losses caused by the same shock by about 4.5%. The loss difference amounts to 0.79 basis points of the counterfactual economy's initial credit stock. Roughly two-thirds of this difference comes from changes in credit allocation. In addition, the net change in aggregate credit is small because borrowing adjustments partially offset each other across risk groups, while lending becomes more concentrated among firms that generate higher credit losses.

A temporary improvement in assessments also leaves lasting exposure to future downturns. The average assessment advantage halves in about four years, but additional credit losses under the same future shock peak in year five and take a further nineteen years to halve.

I then examine the effects of adverse productivity and bank capital shocks within a general equilibrium framework. Aggregate prices are allowed to adjust, while each economy starts from its inherited firm distribution and retains its current pricing rule. Productivity shocks reduce firms' earnings and repayment prospects, whereas bank capital shocks reduce the net worth of financial intermediaries and raise the required return on loans. For the shock sizes considered, the cumulative three-year investment contraction is about 2.5% larger under assessment-based pricing than under fundamentals-based pricing after a productivity shock, compared with 8.4% larger after a bank capital shock.

To investigate this difference, I compare economies using the same aggregate price paths while varying the initial firm distribution and current pricing rule separately. In these comparisons, loan pricing during the downturn explains most of the additional investment decline following a bank capital shock. After a productivity shock, a more optimistic assessment can mitigate the deterioration in repayment prospects perceived by lenders. When a bank capital shock raises the required return, however, the same assessment can make debt prices more sensitive to this increase because lenders expect repayments to continue for longer.

These findings offer two key lessons for financial stability monitoring. First, credit assessment errors can quietly shift risk to vulnerable borrowers even when total lending grows only modestly, leaving behind a legacy of debt that outlives the initial good ratings. Second, the real economic damage caused by this friction depends heavily on the trigger of the downturn. In the model, rating bias amplifies investment contractions much more severely during a bank capital shock than a productivity shock. Consequently, financial stability analysis must look beyond aggregate credit to track how risks quietly accumulate during booms and how different crises alter firm financing.

Related Literature. This paper builds on the literature on credit ratings and corporate financing. Studies of changes in rating criteria and institutional arrangements provide evidence that ratings affect borrowing costs and access to finance (Kisgen and Strahan, 2010; Baghai et al., 2014; Almeida et al., 2017; Kisgen, 2019). Financing conditions can in turn affect borrower survival, creating feedback between ratings and the risks they reflect (Manso, 2013). Using a risk benchmark constructed from firms' financial information, I examine how agency ratings relate to borrowing costs and debt growth among firms with similar fundamentals-based risk. I then use a dynamic model to trace how these financing decisions shape the debt firms carry into a downturn.

The paper also relates to research on beliefs and credit cycles. Credit-market sentiment can predict subsequent changes in financing conditions and economic activity (López-Salido et al., 2017). Models of belief formation explain how optimism sustains favorable financing conditions and generates subsequent reversals (Bordalo et al., 2018, 2026). Easier financing can also reduce current defaults and reinforce optimistic beliefs (Greenwood et al., 2019), while gradual capital structure adjustment makes firms' financial positions persistent (Ippolito et al., 2022). I complement this literature by quantifying the credit-risk exposure inherited from past financing choices. This exposure can persist after the initial assessment advantage has dissipated. By comparing financing histories under the same subsequent shock and pricing rule, I distinguish this inherited exposure from the effects of loan pricing during the downturn.

Another strand of research focuses on how the allocation of credit and the sectors to which it flows influence financial vulnerability. The risk profile of borrowers and the sectoral composition of credit offer insights into future financial stress and economic activity that go beyond what can be gleaned from observing aggregate credit growth alone (Greenwood and Hanson, 2013; Brandão-Marques et al., 2022; Müller and Verner, 2024). As research on credit allocation during crises and the cyclicality of firms suggests, the impact of firm-level heterogeneity on macroeconomic outcomes also depends on the relative weight of these firms within the broader economy (Huneeus et al., 2022; Crouzet and Mehrotra, 2020). This paper links credit assessments to the allocation of credit prior to economic downturns and quantifies the resulting effects on future losses. Financing decisions driven by these credit assessments concentrate more credit among firms in higher-risk states. This shift in allocation accounts for most of the additional credit losses under the same future shock. The impact on aggregate investment depends on the source of the shock. High-risk firms account for most of the additional credit losses under the common recession scenario but undertake only a small share of total investment. Aggregate investment amplification is modest following a productivity shock. Following a bank capital shock, changes in current loan pricing also affect low-risk firms that undertake a large share of investment, producing stronger aggregate amplification.

Section 2 presents the empirical evidence on agency ratings, fundamentals-based risk, and firm financing. Section 3 develops the model, and Section 4 describes its calibration and validation. Section 5 examines how credit assessments shape credit allocation and persistent exposure to future losses. Section 6 studies the aggregate effects of productivity and bank capital shocks and separates the roles of inherited financial positions and current loan pricing. Section 7 concludes.

2 Ratings, Fundamentals, and Firm Financing

Using D&B ratings and Norwegian firm accounts for 2008–2017, I show that, among firms with the same agency rating, weaker fundamentals-based ratings are associated with higher observed bankruptcy rates in the following year. At a given fundamentals-based rating, financing varies with the agency rating. I document three facts. Fact 1: within an agency rating, firms whose fundamentals point to a worse grade fail more often; one grade of disagreement comes with 3.3 times the odds of bankruptcy in the next year. Fact 2: among firms with the same fundamentals-based rating, a one-grade more favorable agency rating comes with a borrowing cost 60 basis points lower. Fact 3: these firms also hold more bank debt; their debt grows faster and they are more likely to have a long-term bank loan. The financing differences are largest among small firms.

2.1 Data and D&B Ratings

The accounts come from Regnskapsdatabasen, the annual financial statements that Norwegian limited-liability firms (AS and ASA) file with the Brønnøysund Register Centre, as compiled by SNF. From 1999 to 2018 they cover 3,718,022 firm-years of 423,113 firms. Almost all are small and privately held: listed firms account for 0.075 percent of firm-years, and the median firm has assets of about NOK 2.5 million.

Dun & Bradstreet (D&B) assigns Norwegian firms credit grades from AAA to C. The agency describes its rating system as assessing the probability that a firm with a given grade will declare bankruptcy within one year (Dun & Bradstreet, 2012). The ratings are sold to subscribers, including banks, suppliers and other counterparties. The rated firm neither requests nor influences its rating, unlike the issuer-paid ratings of S&P and Moody's.

A bankruptcy is dated by the year in which forced liquidation proceedings open, as recorded in the bankruptcy register. Once proceedings open, management can no longer dispose of the firm's assets. A court-appointed administrator manages the estate, realizing assets and distributing the proceeds to creditors. The administrator may continue operations or sell all or part of the business to a new owner (Altinn, 2023).

Ratings are available from 2005. The measurement sample covers 2008–2017, allowing earlier rated years to be used to set grade boundaries and standardize variables. It contains 2,073,249 firm-years of 346,251 firms with standard agency ratings and 556 bankruptcies in the following year. Observed bankruptcy rates decline as agency ratings improve. Because bankruptcy is rare in both AA and AAA, I pool them as AA+, yielding four grades: C, B, A and AA+.

Table 2.1 describes the 2008–2017 measurement sample. Mean assets are NOK 47.11 million, far above the median of NOK 2.70 million. Among firm-years with observed

Table 2.1: Summary Statistics and Firm Characteristics by Agency Rating

Panel A: Overall summary statistics

Variable	*N*	Mean	SD	P10	Median	P90
Total assets (NOK m)	2,073,249	47.11	1,891.09	0.17	2.70	31.09
Firm age (years)	2,073,249	10.6	12.4	1.0	7.0	24.0
Leverage	2,069,079	4.128	285.818	0.039	0.645	1.110
Operating ROA	2,073,249	-0.213	27.382	-0.194	0.009	0.296
Cash / assets	2,067,671	0.260	0.322	0.001	0.128	0.763
Interest-bearing debt / assets	2,068,619	2.266	126.640	0.000	0.019	0.859
Bank and bond debt / assets	2,070,301	0.373	42.416	0.000	0.000	0.597

Panel B: Firm characteristics by agency rating

	All	C	B	A	AA+
Firm-years	2,073,249	66,884	407,456	809,766	789,143
Share of sample (%)	100.0	3.2	19.7	39.1	38.1
Median assets (NOK m)	2.70	0.85	1.00	2.00	6.06
Mean leverage	4.128	17.470	16.054	0.510	0.547
Mean operating ROA	-0.213	-1.707	-1.060	-0.002	0.134
Mean cash / assets	0.260	0.170	0.214	0.270	0.283
No interest-bearing debt (%)	48.0	40.3	36.4	56.7	45.6
No bank or bond debt (%)	68.4	59.6	62.2	76.0	64.5
Has a long-term bank loan (%)	26.6	30.0	29.7	20.3	31.1
Next-year bankruptcy (%)	0.027	0.238	0.047	0.018	0.007

Notes: The sample contains 2,073,249 firm-years in 2008–2017; AA+ combines AA and AAA. Statistics give equal weight to each firm-year and use nonmissing values for each variable before winsorization or standardization. Assets are in nominal NOK million; ratios are fractions. Leverage is total liabilities over assets; operating ROA is operating profit over assets. Bank and bond debt includes short- and long-term bank loans and bonds. Zero-debt shares use observations with all components of the debt measure observed and nonnegative; rating shares use the full sample. Appendix A.1 provides variable definitions, cleaning rules and observation counts.

debt measures, 48.0 percent have no interest-bearing debt and 68.4 percent have no bank or bond debt. Firms without bank or bond debt can still have other interest-bearing liabilities.

Firms with higher agency ratings are larger and, on average, more profitable. Median assets rise from NOK 0.85 million in C to NOK 6.06 million in AA+. Leverage and bank-loan participation do not follow the same ordering. Long-term bank loans are recorded in 20.3 percent of A-rated firm-years, compared with 30.0 percent in C and 31.1 percent in AA+. Appendix A.1 reports variation within each grade and compares the measurement sample with the smaller financing sample.

2.2 Financial Characteristics Predict Bankruptcy within Agency Ratings

Agency ratings group firms into a few risk categories. I test whether financial characteristics predict observed bankruptcy in the following year among firms with the same agency rating in the same year. Let R_{it}^{A} be firm i's agency rating in year t and $d_{i,t+1}$ an indicator for bankruptcy in $t+1$. I estimate

$$d_{i,t+1} = \lambda_{R_{it}^{A},\,t} + Z_{it}'\beta + \varepsilon_{i,t+1}, \tag{1}$$

where $\lambda_{R_{it}^{A},\,t}$ denotes agency-rating-by-year fixed effects. I include a separate intercept for each agency rating in each year. These intercepts allow bankruptcy probabilities to differ freely across ratings and years. Agency ratings C, B, A and AA+ are coded 1, 2, 3 and 4, respectively. The specification includes all rating-by-year cells in 2008–2017 and no additional overall intercept. The vector Z_{it} contains eight characteristics (leverage, operating return on assets, interest coverage, cash over assets, log assets, firm age, asset growth and the short-term share of liabilities). I use firm-years with all eight characteristics observed. The estimation sample covers 2008–2017 and contains 1,019,223 firm-years from 222,128 firms, with 214 bankruptcies in the following year. Standard errors are clustered by firm.

The eight financial characteristics jointly predict next-year bankruptcy within agency ratings and years (Wald $\chi^2(8) = 50.55$, $p < 0.001$). Appendix Table A.4 reports the estimates. The characteristics remain jointly significant when AA and AAA are treated separately. They also remain jointly significant at the 5 percent level after adding other accounting variables, debt structure and borrowing costs (Appendix Table A.5).

2.3 A Fundamentals-Based Rating and the Rating Wedge

For each year t, I train and calibrate a bankruptcy prediction model using only accounts dated before t. The agency rating is not a predictor. I apply the model to year-t

accounts and map its predicted probabilities to the agency's rating scale using historical bankruptcy rates. This puts the agency rating and the credit risk implied by firms' accounts on the same scale.

Predicted risk. The gradient-boosted classifier predicts bankruptcy in the next calendar year from eighteen variables: balance-sheet structure, profitability, debt service, growth, investment, age, employment, industry, the accounting standard and the interbank rate. The historical sample includes firms without a standard agency rating. I fit the model on the earlier account years and calibrate its scores to observed bankruptcy frequencies in the most recent years of that sample (Appendix A.3). Let $\widehat{p}_{it}$ denote the resulting prediction for firm i in year t.

Ratings. Let p_t^g be the one-year bankruptcy rate of agency rating g in the rated years before t. The boundary between adjacent grades is the geometric mean of their rates,

$$c_{g,g+1,t} = \sqrt{p_t^g \, p_t^{g+1}}, \tag{2}$$

and the fundamentals-based rating R_{it}^F is the grade whose interval contains $\widehat{p}_{it}$. A fundamentals-based rating of B thus means that the firm's predicted risk lies in the range of historical risk that the agency's scale assigns to B.

The fundamentals-based rating has a higher area under the receiver operating characteristic curve (AUC) than the agency rating, at 0.782 versus 0.756 in the pooled 2008–2017 sample (Appendix Table A.7).

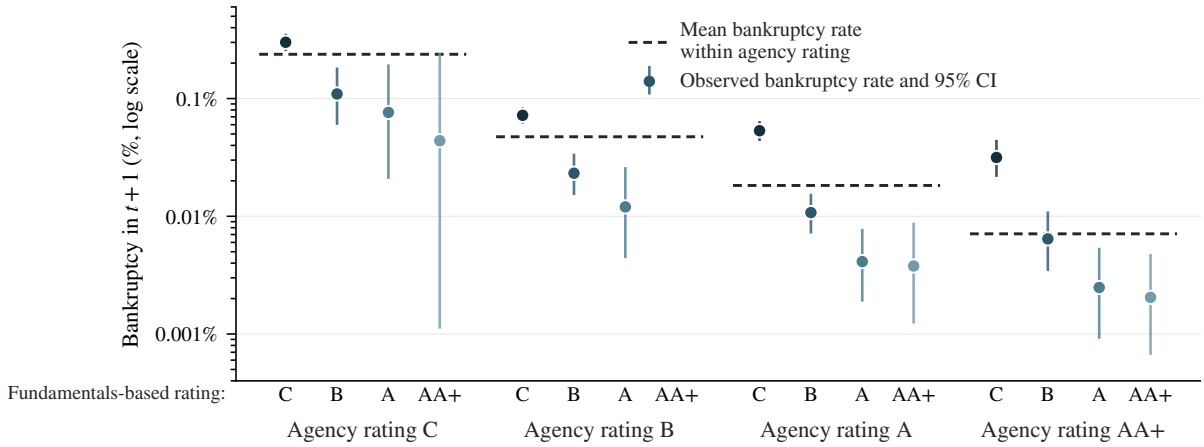
Each year, I screen the 10 percent of firms with the highest $\widehat{p}_{it}$. This captures 57.5 percent of next-year bankruptcies, compared with 40.6 percent using agency ratings (Appendix Figure A.1).

Within each agency rating, observed next-year bankruptcy rates decline as the fundamentals-based rating improves (Figure 2.1). Among firms rated A by the agency, the observed next-year bankruptcy rate is 0.053 percent for fundamentals-based rating C and 0.0038 percent for AA+, a fourteenfold difference.

Even within the agency's highest grade, bankruptcies are concentrated among firms with weak fundamentals. Among AA+-rated firms, those with fundamentals-based rating C make up 13 percent of firm-years but account for 57 percent of next-year bankruptcies.

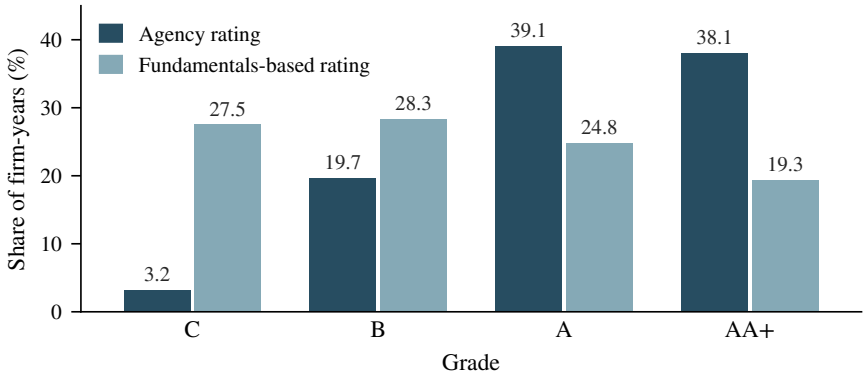
Firms with a higher agency rating can also have a higher bankruptcy rate when their fundamentals are weaker. Firms rated AA+ by the agency and C on fundamentals have a next-year bankruptcy rate of 0.032 percent, compared with 0.011 percent for firms rated A by the agency and B on fundamentals.

Figure 2.1: Bankruptcy by Fundamentals-Based Rating within Agency Ratings



Notes: Bankruptcy rate in $t+1$ for each combination of agency rating (groups) and fundamentals-based rating (points), 2,073,249 firm-years, 2008–2017; log scale. Dashed lines show the observed next-year bankruptcy rate within each agency rating, calculated as total bankruptcies divided by total firm-years over 2008–2017. Vertical lines: exact Poisson 95 percent intervals. The cell with agency rating B and fundamentals-based rating AA+ contains 22,009 firm-years and no observed bankruptcies in the following year. Its zero bankruptcy rate is omitted from the logarithmic plot. Counts in Appendix Table A.8.

Figure 2.2: Grades under the Two Ratings



Notes: Share of the 2,073,249 firm-years in each grade, 2008–2017, under the agency rating and under the fundamentals-based rating. AA+ pools AA and AAA.

The rating wedge. I code both ratings as C = 1, B = 2, A = 3 and AA+ = 4 and define the rating wedge

$$W_{it} = R^A_{it} - R^F_{it} \in \{-3, \ldots, 3\}. \tag{3}$$

A positive wedge means that the agency rating is more favorable than the fundamentals-based rating; zero means that the two ratings agree. They agree for 30 percent of firm-years (Figure 2.2; Appendix Table A.8). The agency places 77 percent of firm-years in A or AA+, while the fundamentals-based ratings are spread over all four. The average wedge depends on predicted-risk calibration and the grade boundaries. I compare firms within agency ratings or fundamentals-based ratings in the same year. The one-year correlation of the wedge is 0.37, and it remains unchanged in 36.6 percent of consecutive firm-year pairs.

2.4 Fact 1: The Wedge Predicts Bankruptcy within Agency Ratings

Fact 1. Among firms with the same agency rating, those whose fundamentals point to a worse grade are more likely to go bankrupt.

I estimate two logit regressions of bankruptcy in $t+1$. The first uses the rating wedge. The second compares the top- and bottom-quartile groups of predicted next-year bankruptcy probability, $\widehat{p}_{it}$, within each agency rating and year. The dummy H_{it} equals one for the top group and zero for the bottom group, which is the reference group; only these two groups enter the second regression.[1]

$$\operatorname{logit}\Pr(d_{i,t+1}=1) = \alpha + \beta_W W_{it} + \lambda_{R^A_{it}} + \delta_t, \tag{4}$$

$$\operatorname{logit}\Pr(d_{i,t+1}=1) = \alpha + \beta_H H_{it} + \lambda_{R^A_{it}} + \delta_t, \tag{5}$$

where $\lambda_{R^A_{it}}$ denotes agency-rating fixed effects. Rating C is the reference category, with its effect normalized to zero. The rating effects are constant across years. The term δ_t denotes year fixed effects. Neither specification includes firm fixed effects, and standard errors are clustered by firm.

Table 2.2 reports the estimates. Holding agency rating and year fixed, a one-grade increase in the wedge corresponds to a one-grade deterioration in the fundamentals-based rating and is associated with 3.34 times the odds of bankruptcy in the following year. Firms in the top-quartile predicted-risk group have 6.75 times the odds of those in the bottom-quartile group. The full-sample four-group regression also shows increasing estimated odds across predicted-risk groups (Appendix Table A.10). The relation holds at longer horizons: one grade of wedge comes with 35 to 46 percent higher odds of bankruptcy two to five years later (Appendix Table A.11). It also rises step by step with the gap: relative to firms whose ratings agree, the odds ratio is 0.37 for a wedge of -1, 3.1 for +1 and 13 for +2 (Appendix Table A.12).

2.5 Facts 2 and 3: Financing at a Given Fundamentals-Based Rating

Fact 2. Among firms with the same fundamentals-based rating, a more favorable agency rating comes with a lower borrowing cost.

Fact 3. Among the same firms, a more favorable agency rating comes with more bank debt.

For an outcome $Y_{i,t+1}$, I estimate

$$Y_{i,t+1} = \beta W_{it} + \lambda_{R^F_{it},\,t} + \delta_{j(i,t),\,t} + X'_{it}\gamma + u_{i,t+1}, \tag{6}$$

[1]The top group includes values at or above the within-agency-rating-year 75th percentile; the bottom group includes values at or below the 25th percentile. All ties at the cutoffs are retained.

Table 2.2: The Rating Wedge and Next-Year Bankruptcy within Agency Ratings

	Bankruptcy in $t+1$ (logit)	
	(1)	(2)
Rating wedge W_{it}	1.205***	
	(0.092)	
High predicted risk H_{it}		1.909***
		(0.140)
Odds ratio	3.34	6.75
95% interval of the odds ratio	[2.79, 4.00]	[5.13, 8.89]
Agency-rating effects	Yes	Yes
Year effects	Yes	Yes
Firm-years	2,073,249	1,351,328
Firms	346,251	332,069
Bankruptcies	556	419

Notes: Logit estimates of equations (4) and (5). The outcome is formal bankruptcy (*konkaar*) in the calendar year after the rating year t, 2008–2017. $W_{it} = R^A_{it} - R^F_{it}$, with grades coded C = 1 to AA+ = 4. $H_{it} = 1$ if the firm's predicted bankruptcy probability is at or above the 75th percentile of its agency-rating-by-year cell and $H_{it} = 0$ if it is at or below the 25th percentile; column (2) uses only these two groups, and ties stay together. Both columns include additive effects for the four agency ratings and for years. Standard errors clustered by firm in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

where $\lambda_{R^F_{it},t}$ denotes fundamentals-based-rating-by-year fixed effects. These effects allow each fundamentals-based grade's effect to vary across years. The term $\delta_{j(i,t),t}$ denotes industry-by-year fixed effects, where $j(i,t)$ is firm i's industry in year t. With R^F_{it} held fixed, the wedge moves one for one with the agency rating, so β compares firms with the same fundamentals-based rating, industry and year whose agency ratings differ by one step. The controls X_{it} measure size, asset tangibility, profitability, sales, cash, cash earnings, leverage and the composition of the firm's debt at t, including its bank loans. The controls also include a cubic in the log predicted probability of next-year bankruptcy, $\widehat{p}_{it}$, to account for variation in predicted risk within each fundamentals-based rating.

Four outcomes, all measured at $t+1$, share one sample, one set of controls and one set of weights. Borrowing cost is interest expense divided by interest-bearing debt and measures the average cost of outstanding debt. Debt D is the sum of long- and short-term bank loans and bonds, and its growth is the symmetric rate

$$g_{i,t+1} = \frac{D_{i,t+1} - D_{it}}{(D_{i,t+1} + D_{it})/2} \times 100, \tag{7}$$

which lies between −200 and 200 and counts a firm that starts to borrow as +200. The other two outcomes indicate whether the firm has bank or bond debt and whether it has

Table 2.3: Borrowing Cost and Bank Debt at a Given Fundamentals-Based Rating

	Borrowing cost (bp) (1)	Debt growth (pp) (2)	Has bank or bond debt (pp) (3)	Has long-term bank loan (pp) (4)
Rating wedge W_{it}	−60.18***	0.98***	0.76***	0.75***
	(3.52)	(0.15)	(0.07)	(0.07)
Mean of the outcome	555	3.59	61.4	50.6
Firm controls	Yes	Yes	Yes	Yes
Rating × year effects	Yes	Yes	Yes	Yes
Industry × year effects	Yes	Yes	Yes	Yes
Firm-years	996,989	996,989	996,989	996,989
Firms	172,489	172,489	172,489	172,489

Notes: Weighted least squares estimates of equation (6); all four columns use the same firm-years, controls, fixed effects and weights. Rating: the fundamentals-based rating R^F_{it}. Outcomes are measured at $t+1$. Borrowing cost: interest expense over interest-bearing debt, winsorized at the annual 1st and 99th percentiles. Debt D: long- and short-term bank loans plus bonds; growth $g = (D_{t+1} - D_t)/[(D_{t+1} + D_t)/2] \times 100$, zero when both are zero. Columns (3) and (4) are indicators for $D_{t+1} > 0$ and for long-term bank loans $L_{t+1} > 0$, times 100. The sample contains firm-years with interest-bearing debt at $t+1$, which the borrowing cost requires. Controls and weights are listed in Appendix A.5; means use the same weights. Standard errors clustered by firm in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

a long-term bank loan. The borrowing cost requires interest-bearing debt at $t+1$; the sample is the 996,989 firm-years of 172,489 firms that meet this condition. Within each fundamentals-based rating, the weights give the firm-years in which the two ratings agree the same total weight as those in which they disagree (Appendix A.5).

Table 2.3 reports the estimates. A one-grade more favorable agency rating comes with a borrowing cost 60 basis points lower, about 11 percent of the mean cost of 5.6 percent.

The linear specification assumes the same borrowing-cost difference for each additional grade of wedge. I allow this difference to vary by replacing W_{it} with an indicator for each nonzero wedge value. Firms whose ratings agree, $W_{it} = 0$, form the comparison group. Borrowing costs are 110, 130 and 136 basis points lower at wedges of +1, +2 and +3, respectively (Appendix Table A.13).

I then estimate a separate borrowing-cost difference for each rating pair. Each pair is compared with firms in the same fundamentals-based rating and year whose ratings agree. Among firms with fundamentals-based rating C, those rated B by the agency pay 278 basis points less than those rated C by the agency. The corresponding one-grade differences are 30 basis points in fundamentals-based rating B and 11 in grade A (Appendix Table A.14). The same one-grade gap thus comes with a much larger borrowing-cost advantage among firms with the weakest fundamentals.

The same firms hold more bank debt. Per grade of wedge, their debt grows 0.98 percentage points faster, against mean growth of 3.6 points; the probability that they

have bank or bond debt is 0.76 points higher; and the probability that they have a long-term bank loan is 0.75 points higher. The two probabilities rise by almost the same amount, so the higher probability of borrowing is a higher probability of holding a long-term bank loan.

Firms' accounts reveal differences in default risk within agency ratings. Within each fundamentals-based rating, firms with more favorable agency ratings pay less to borrow and are more likely to hold long-term bank loans. This pattern is consistent with lenders using agency ratings to price and allocate credit.

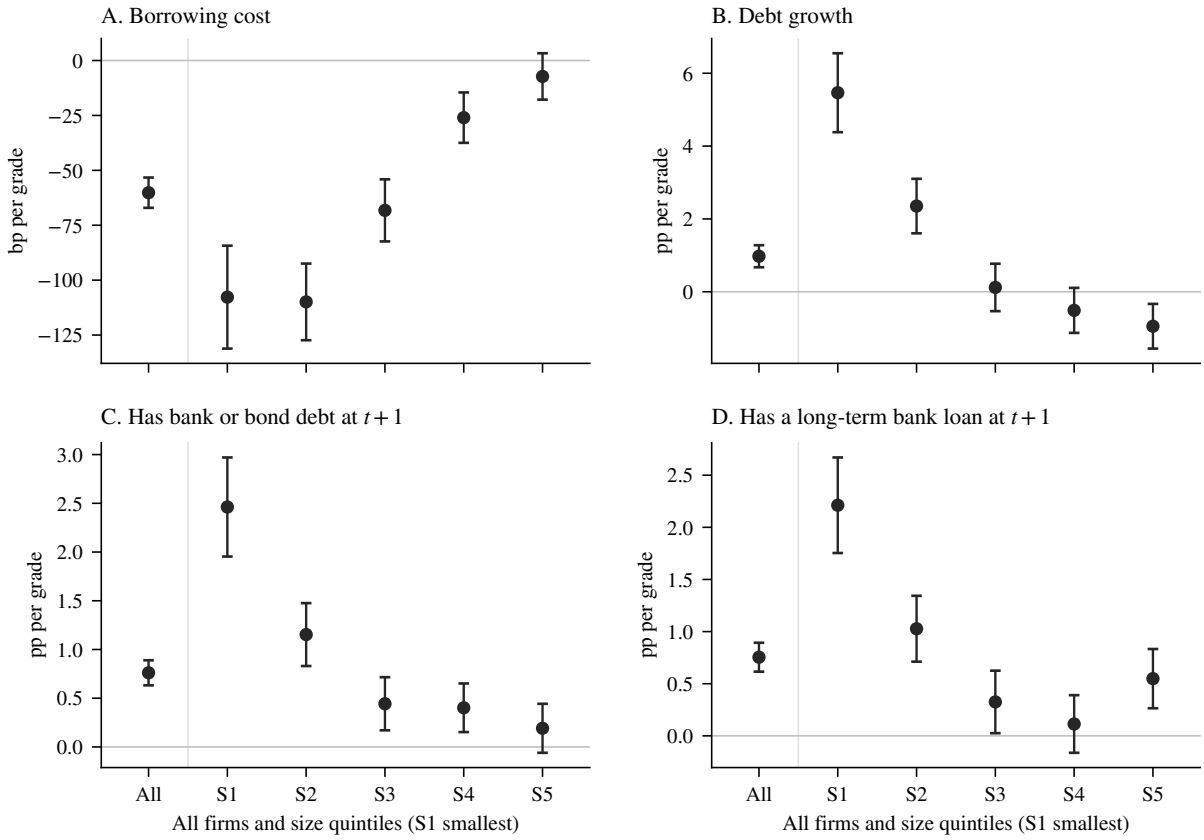
2.6 Who Borrows More, and at What Maturity

The differences in Table 2.3 are concentrated in small firms. Figure 2.3 re-estimates equation (6) with the wedge, the controls and the rating-by-year effects interacted with five size groups, the quintiles of total assets among rated firms in each year. Per grade of wedge, the borrowing cost is 108 and 110 basis points lower in the two smallest quintiles, 26 basis points lower in the fourth and 7 basis points lower, not significantly, in the largest. Debt grows 5.5 percentage points faster in the smallest quintile and 2.4 points faster in the second, and the probability of having bank or bond debt is 2.5 and 1.2 points higher. In the smallest quintile, median assets are NOK 0.2 million, 72 percent of firm-years start the year without bank or bond debt, and 57 percent have fundamentals-based rating C. Borrowing participation is an important margin for these firms. The largest quintile, with median assets of NOK 33 million, holds 94 percent of bank and bond debt (Appendix Table A.15).

The largest financing differences occur among small firms, while large firms hold most of the debt. The aggregate implications depend on how much debt each size group holds and how financing varies within it.

Firms with more favorable agency ratings are more likely to hold long-term bank loans in every size quintile. Per grade, the probability is 2.2 percentage points higher in the smallest quintile and 0.55 points higher in the largest; only the estimate for the fourth quintile is not significant (Figure 2.3, Panel D). Long-term bank loans grow faster in the four smallest quintiles and do not fall in the largest, while outside the smallest quintile short-term bank loans grow 1.5 to 3.3 points more slowly per grade (Appendix Table A.15, Panel B). In the largest firms, a more favorable grade thus goes with longer-maturity bank debt rather than more of it: their total debt grows slightly more slowly (0.95 points per grade), and the mix shifts from short-term to long-term loans. Long-term borrowing links current financing conditions to repayment obligations in later years.

Figure 2.3: Borrowing Cost and Bank Debt by Firm Size



Notes: Coefficients on the rating wedge in equation (6), per grade, with 95 percent intervals. "All" repeats Table 2.3; S1–S5 are quintiles of total assets among rated firm-years, computed year by year (S1 smallest), with the wedge, the controls and the fundamentals-based-rating-by-year effects interacted with the quintile. Outcomes at $t + 1$ as in Table 2.3; same sample and weights. Standard errors clustered by firm. Estimates in Appendix Table A.15.

2.7 Bankruptcy after Upgrades

Facts 1–3 compare firms. Within firms, an agency upgrade at an unchanged fundamentals-based rating is followed first by fewer bankruptcies and later by more. I compare years in which the agency raises a firm's rating by one step with years in which it leaves the rating unchanged, holding the fundamentals-based rating fixed, with firm effects and effects for each initial pair of grades and year (Appendix A.6). After an upgrade, cumulative bankruptcy is 1.93 percentage points lower by year three. In year five, bankruptcy is 0.86 percentage points more likely after an upgrade, and the cumulative gap has narrowed to 1.17 points. Upgraded firms also face a heavier interest burden. By year five, interest expense relative to pre-upgrade assets has risen by 0.38 percentage points more than for firms whose agency rating is unchanged. The probability that operating profit falls short of interest expense has risen by 5.1 points more.

The pattern suggests that easier financing may help firms survive initially while leaving them with more interest to pay later.

3 Quantitative Model

I develop an annual model of heterogeneous firms and financial intermediaries to study how credit assessments affect borrowing, investment, and exposure to future downturns. The firm financing problem is closely related to Khan, Senga, and Thomas (2016) and Ottonello and Winberry (2020): firms jointly choose capital and debt, cannot issue equity, and default only when no admissible investment and financing plan satisfies the nonnegative-payout constraint. Here, long-term debt, capital and debt adjustment costs, and a separate investment-financing restriction also shape feasible choices. A persistent rating wedge shifts lenders' productivity forecasts, while firms make decisions under the true productivity process. Credit assessments therefore affect debt prices without directly changing production technology.

Foreign-owned intermediaries finance their corporate debt portfolios with net worth and foreign borrowing. I adapt the net-worth accumulation and incentive constraint of Gertler and Karadi (2011) to this setting. Loan losses and changes in the market value of outstanding claims can affect intermediary net worth and lending capacity. The quantitative exercises compare general-equilibrium responses and use common price paths to separate inherited firm distributions from the pricing rule applied during the downturn.

3.1 Environment

Time is discrete and runs forever. A period corresponds to one year. The economy is populated by a continuum of firms, competitive foreign-owned financial intermediaries, and a representative household. Foreign investors supply wholesale funding at the gross rate R^*. The final good is the numeraire.

Firms differ in productivity, capital, debt, and the rating wedge. They face idiosyncratic productivity and cash-flow risk. The rating wedge affects the productivity distribution that lenders use to price debt; it does not change the distribution that generates firms' realized productivity. The household supplies labor and owns the firms. Foreign owners receive distributions from intermediaries and provide capital to entering bankers. Foreign ownership determines these equity flows; foreign wholesale funding determines intermediaries' borrowing costs.

Aggregate uncertainty is absent in the stationary economy. To study a recession, I introduce an unanticipated decline in the aggregate productivity index A_t. After the initial shock, the recovery path is deterministic:

$$\log A_{t+1} = \rho_A \log A_t, \qquad A_0 < 1, \quad 0 \leq \rho_A < 1. \tag{8}$$

The economy is initially in a stationary equilibrium with $A = 1$. Once the shock occurs, agents know its subsequent path. Time subscripts on value functions and prices incorporate this aggregate path. Throughout the quantitative exercises, a TFP shock means a change in this index A_t; the coefficient in physical production is $A_t^{1-\nu}$.

Timing. At the beginning of a period, firms that remain in operation observe their productivity, rating wedge, and cash-flow shock. They choose whether to operate and, conditional on operation, choose labor, next-period capital, and debt. Payments on outstanding debt and the issuance or repurchase of debt occur at current prices. Between operating periods, a firm exits exogenously with probability π_x. Entrants replace firms that default or exit, keeping the mass of firms constant. New firms start production in the following period. Current debt prices, default decisions, intermediary net worth, and the lending spread are determined jointly in equilibrium.

3.2 Firms

The state of an incumbent firm is $x = (z, W, k, b)$, where z is idiosyncratic productivity, W the rating wedge, $k > 0$ installed capital, and $b \geq 0$ the face value of outstanding debt. Firms choose labor at the current wage and finance investment with operating income and long-term debt.

Technology. An operating firm produces according to

$$y_t = (A_t z)^{1-\nu} k^{\alpha(1-\nu)} \ell^{\nu}, \qquad \alpha, \nu \in (0,1). \tag{9}$$

The sum of the capital and labor elasticities is less than one. This gives firms decreasing returns to scale and a finite desired size. Labor is chosen within the period at wage w_t. Maximizing output net of the wage bill gives

$$\ell_t(z,k) = \left(\frac{\nu}{w_t}\right)^{1/(1-\nu)} A_t z k^{\alpha}, \tag{10}$$

$$\pi_t^o(z,k) = \Theta_t z k^{\alpha} - F, \qquad \Theta_t = (1-\nu) A_t \left(\frac{\nu}{w_t}\right)^{\nu/(1-\nu)}. \tag{11}$$

Here F is a fixed operating cost. At the reference wage $\bar{w} = \nu(1-\nu)^{(1-\nu)/\nu}$ and $A = 1$, $\Theta = 1$ and operating profits reduce to $zk^{\alpha} - F$. Thus α is the capital exponent after labor has been optimized out. The normalization of A_t is in the same units as this reduced-form return.

Investment and debt adjustment. Capital depreciates at rate δ. Investment and its adjustment cost are

$$i(k',k) = k' - (1-\delta)k, \qquad \Psi_k(k',k) = \frac{\phi_k}{2}\left(\frac{i(k',k)}{k}\right)^2 k. \tag{12}$$

Firms can invest or sell capital. They also pay a cost when changing the face value of debt:

$$\Psi_b(b',b) = \begin{cases} \dfrac{\phi_b^+}{2}(b'-b)^2, & b' \geq b, \\ \dfrac{\phi_b^-}{2}(b'-b)^2, & b' < b, \end{cases} \qquad \phi_b^- > \phi_b^+ > 0. \tag{13}$$

I follow Ippolito et al. (2022) in allowing asymmetric debt adjustment costs. The piecewise-quadratic specification above makes debt reductions more costly than debt increases, slowing deleveraging after adverse shocks. These costs capture limited financial flexibility beyond the incentives generated by the pricing of outstanding debt.

Long-term debt. A fraction γ of each unit of debt matures every period. Conditional on repayment, lenders receive $c + \gamma$ and retain a claim to the remaining $1 - \gamma$ units. The coupon c is fixed. If the firm chooses next-period face value b', net issuance is

$$n(b',b) = b' - (1-\gamma)b. \tag{14}$$

A negative value of n denotes a repurchase. Let $q_t(z, W, k', b')$ be the price per unit of face value. Lenders condition on the firm's chosen capital and debt because both affect future repayment. The same price applies to new and surviving claims of equal seniority.

Excluding the cash-flow shock, the payout associated with a choice (k', b') is

$$\begin{aligned} d_t^0(x, k', b') = \Theta_t z k^\alpha - F - (c + \gamma)b + q_t(z, W, k', b')n(b', b) \\ - i(k', k) - \Psi_k(k', k) - \Psi_b(b', b). \end{aligned} \tag{15}$$

The firm receives a cash-flow shock $m = \sigma_m k^\alpha \varepsilon^m$, where $\varepsilon^m \sim \mathcal{N}(0, 1)$ is independent across firms and time and independent of productivity and the rating wedge. The shock does not directly change installed capital or the recovery value conditional on k and b. The firm's payout is $d_t = d_t^0 + m$. As in Ottonello and Winberry (2020), firms cannot issue external equity and payouts must be nonnegative. Debt is therefore the only source of external finance. The model has no separate liquid asset, and d_t measures cash distributed outside the firm; it need not coincide with reported dividends.

Investment financing. A fraction ω_I of positive investment must be financed with current bank borrowing. With $[a]_+ = \max\{a, 0\}$, the restriction is

$$\omega_I [i(k', k)]_+ \leq q_t(z, W, k', b')[n(b', b)]_+. \tag{16}$$

When $\omega_I = 0$, this restriction is vacuous. It also leaves firms that disinvest free to repurchase debt. For an investing firm, a lower debt price reduces the cash raised by a given issuance and can restrict feasible capital expenditure. The requirement concerns investment rather than the wage bill, so its direct effect on productive capacity starts in the following period. Labor and the set of operating firms can nevertheless adjust immediately.

Costly bank monitoring provides a rationale for linking investment to bank funding. In Chakraborty and Ray (2006) and Chakraborty (2019), sufficient bank funding makes monitoring incentive compatible, reducing entrepreneurial moral hazard and helping firms obtain funds from other investors. I impose the link in reduced form. The restriction applies to all investing firms, including those with sufficient internal funds, and counts issuance that replaces maturing debt. These are maintained assumptions of the model.

Value of operation. Let $\mathcal{A}_t(x)$ be the set of positive capital and non-negative debt choices satisfying (16). The firm observes m before choosing (k', b'). Conditional on

repayment, it solves

$$V_t^R(x,m) = \max_{\substack{(k',b')\in\mathcal{A}_t(x) \\ d_t^0(x,k',b')+m\geq 0}} \left\{ d_t^0(x,k',b') + m + \beta_f(1-\pi_x)\mathbb{E}_t[V_{t+1}(z',W',k',b')] \right\}. \quad (17)$$

The expectation uses the true productivity and wedge transitions. Firms know how lenders price their debt, but do not adopt lenders' productivity beliefs. The factor $1-\pi_x$ accounts for exogenous exit before the next operating period. Equity receives zero on exit or default. The value before the cash-flow shock is

$$V_t(x) = \mathbb{E}_m \left[\max\{0, V_t^R(x,m)\} \right]. \quad (18)$$

An empty feasible set has repayment value $-\infty$. I break ties in favor of repayment.

Default. Feasible repayment choices yield nonnegative payouts and continuation values. The firm repays when indifferent, so it defaults only when no admissible choice satisfies the payout constraint. Arellano, Bai, and Kehoe (2019) also use this feasibility criterion for default. Define

$$d_{\max,t}(x) = \max_{(k',b')\in\mathcal{A}_t(x)} d_t^0(x,k',b'). \quad (19)$$

Default occurs if $m < -d_{\max,t}(x)$, giving probability

$$p_t^D(x) = \Phi\left(-\frac{d_{\max,t}(x)}{\sigma_m k^\alpha} \right). \quad (20)$$

The cash-flow shock makes default probabilities continuous in the financing margin. It also changes which investment and borrowing choices are feasible, so optimal policies generally depend on the shock's realization.

On default, total recovery is $\mathcal{R}(k,b) = \min\{b, \xi(1-\delta)k\}$. The recovery per unit of debt is $r(k,b) = \mathcal{R}(k,b)/b$ for $b > 0$. I use the same recovery technology for exogenous liquidation. Appendix E.2 describes liquidation and entry accounting.

3.3 Credit Assessments and Beliefs

Under the true transition law, productivity follows

$$\log z_{t+1} = \rho_z \log z_t + (1-\rho_z)\mu_z + \sigma_z \varepsilon_{t+1}^z, \qquad \varepsilon_{t+1}^z \sim \mathcal{N}(0,1). \quad (21)$$

The rating wedge follows a separate process,

$$W_{t+1} = (1 - \rho_W)\mu_W + \rho_W W_t + \sigma_W \varepsilon_{t+1}^W, \qquad \varepsilon_{t+1}^W \sim \mathcal{N}(0, 1), \tag{22}$$

with independent innovations. Here μ_W is the stationary mean, rather than the intercept, of the wedge process.

Lenders use a perceived productivity transition with conditional mean

$$\widetilde{\mathbb{E}}_t[\log z_{t+1}] = \rho_z \log z_t + (1 - \rho_z)(\mu_z + \eta_W W_t), \qquad \eta_W > 0. \tag{23}$$

Its conditional variance is σ_z^2. A positive wedge makes lenders act as if the firm's long-run productivity mean were higher. At $W = 0$, their perceived transition coincides with the true transition. The parameter η_W shifts the long-run mean, so the one-period conditional mean shifts by $(1 - \rho_z)\eta_W W$. Both firms and lenders use the true transition for W and the true cash-flow distribution.

The wedge changes realized outcomes through financing choices. It does not directly change technology, recovery, adjustment costs, or the realization of productivity. In particular, the distribution of firms and the returns earned by intermediaries are evaluated under (21), even when debt prices reflect (23).

Debt pricing. Let e_{t+1} indicate exogenous exit before the next operating period, with probability π_x. Conditional on no exogenous exit, let D_{t+1} indicate default after the cash-flow shock. One unit of incumbent debt purchased at t pays

$$\begin{aligned} X_{t+1} = {} & e_{t+1} r(k', b') \\ & + (1 - e_{t+1}) \left\{ D_{t+1} r(k', b') + (1 - D_{t+1})[c + \gamma + (1 - \gamma) q_{t+1}] \right\}. \end{aligned} \tag{24}$$

The continuation price q_{t+1} is evaluated at the next period's realized state and optimal capital and debt choices. It therefore depends on the next cash-flow shock as well as on productivity and the wedge.

Intermediaries require a perceived gross return $R_t^L = R^* + s_t$, where s_t is the common lending spread. Competition gives

$$q_t(z, W, k', b') = \frac{\widetilde{\mathbb{E}}_t[X_{t+1}]}{R^* + s_t}. \tag{25}$$

The spread compensates for scarce intermediary capacity; firm-specific debt prices also reflect perceived default and recovery. These are distinct components of financing

conditions. The no-default, no-liquidation claim has price

$$\bar{q}_t = \frac{c + \gamma + (1-\gamma)\bar{q}_{t+1}}{R^* + s_t}. \tag{26}$$

This is a useful reference price. With $c = R_f - 1$ and a constant required return R_f, it equals one. Exogenous liquidation with incomplete recovery can lower the price of a claim even when endogenous default is negligible.

3.4 Financial Intermediaries

The intermediary block adapts the net-worth accumulation and incentive constraint of Gertler and Karadi (2011) to portfolios of long-term corporate debt. It retains banker exit and transfers from foreign owners to entering bankers. In this model, intermediaries hold risky debt issued by heterogeneous firms and borrow from foreign investors at the constant gross rate R^*. Bankers discount future payouts at the constant factor β_B.

Intermediaries finance their portfolios with net worth and foreign borrowing. Let S_t denote the market value of their corporate debt portfolio at the end of period t, N_t^B intermediary net worth available for lending, and $\mathcal{F}_t$ foreign funding. Their balance sheet satisfies

$$S_t = N_t^B + \mathcal{F}_t. \tag{27}$$

Intermediaries require a perceived gross return $R^* + s_t$ on corporate debt, where s_t is the common intermediation spread. Firm-specific debt prices additionally reflect perceived repayment and recovery prospects, as in (25).

Intermediaries use lenders' productivity beliefs to price debt and evaluate future payouts. Actual repayments, recoveries, and changes in the market value of surviving claims determine realized returns and net worth. These outcomes are evaluated under the true productivity process, while market prices continue to reflect credit assessments. Let R_{t+1}^B denote the realized gross return on the portfolio purchased at date t. It satisfies

$$R_{t+1}^B S_t = CF_{t+1} + S_{t+1} - \text{Iss}_{t+1}, \tag{28}$$

where CF_{t+1} includes payments and recoveries on outstanding claims, and Iss_{t+1} is the market value of net debt issuance, including entrant debt. Subtracting net issuance isolates the return on the inherited portfolio. Because intermediaries hold long-term debt, this return reflects both current repayments and the market value of surviving claims.

Bankers continue operating with probability θ_B. Exiting bankers transfer their net worth to foreign owners, who provide new bankers with capital equal to $\omega_B S_t$. Let $\mathcal{X}_t$ denote an unanticipated transfer from intermediaries to the rest of the world, deducted

before banker turnover. It is zero except in the bank-capital experiment of Section 6.1. Aggregate intermediary net worth therefore evolves according to

$$N_{t+1}^B = \theta_B \left[R_{t+1}^B S_t - R^*(S_t - N_t^B) - \mathcal{X}_{t+1} \right] + \omega_B S_t. \tag{29}$$

A decline in portfolio returns reduces the net worth available for subsequent lending. This loss occurs even when the foreign funding rate remains unchanged.

Intermediary borrowing is limited by an incentive constraint. A banker can divert a fraction λ_B of assets, at the cost of losing the value of continued operation. Creditors provide funds only when continued operation is at least as valuable as diversion. The resulting constraint takes the form

$$S_t \leq \phi_t N_t^B, \tag{30}$$

where ϕ_t is an endogenous leverage limit.

I focus on equilibria in which the incentive constraint binds. Under the constant banker discount factor β_B and the deterministic aggregate path considered here, the leverage limit satisfies

$$\phi_t = \frac{\beta_B R^* \left(1 - \theta_B + \theta_B \lambda_B \phi_{t+1}\right)}{\lambda_B - \beta_B s_t \left(1 - \theta_B + \theta_B \lambda_B \phi_{t+1}\right)}. \tag{31}$$

The denominator is positive in the equilibria studied. This condition links current lending capacity to the profitability of current lending and the value of future intermediation. More valuable lending opportunities increase the cost of diversion and allow intermediaries to support more assets with a given amount of net worth. The banker's optimization problem and the derivation of (31) are provided in Appendix E.3.

Let S_t^F denote the market value of corporate debt implied by firms' financing decisions, including entrant debt; its aggregation is given in (61). With a positive intermediation spread, credit-market clearing requires

$$S_t^F = \phi_t N_t^B. \tag{32}$$

The spread adjusts jointly with firm borrowing, debt prices, and intermediary net worth to satisfy this condition. Access to foreign funding therefore does not make credit supply perfectly elastic: additional borrowing must remain consistent with intermediaries' incentive constraint.

The rating wedge affects intermediation through debt valuation, firms' financing choices, and the composition of bank portfolios. During a recession, lower repayments and declines in the value of outstanding claims can reduce bank net worth and tighten

financing conditions. The equilibrium spread response depends on both this change in lending capacity and the accompanying change in firms' demand for credit.

3.5 Households and Aggregation

The representative household consumes its current income and supplies labor. I normalize the mass of workers to one, so L_t denotes average hours. The household has preferences

$$\sum_{t=0}^{\infty} \beta_H^t \left[\frac{C_t^{1-\sigma_C}}{1-\sigma_C} - \chi \frac{L_t^{1+\zeta}}{1+\zeta} \right]. \tag{33}$$

Here, C_t is consumption and β_H is the household discount factor. The parameter σ_C governs consumption curvature, $1/\zeta$ is the Frisch elasticity of labor supply, and χ is the weight on labor disutility. The household cannot smooth consumption through an additional saving asset. Firm and banker discount factors are specified separately. The household owns firms but not intermediaries. Its budget is

$$C_t = w_t L_t + \Pi_t^F + \mathcal{L}_t^H - T_t^E, \tag{34}$$

where Π_t^F is the sum of operating-firm payouts, $\mathcal{L}_t^H$ is liquidation revenue left after creditors have been repaid, and T_t^E is the household contribution to entering firms' capital. Net intermediary payouts to foreign owners are

$$\Pi_t^B = (1-\theta_B)\left[R_t^B S_{t-1} - R^* \mathcal{F}_{t-1} - \mathcal{X}_t\right] - \omega_B S_{t-1}. \tag{35}$$

These payouts equal distributions from exiting bankers less the capital provided to entering bankers. Foreign owners receive the distributions and provide entry capital, so net intermediary payouts do not enter domestic household income. The household's labor-supply condition is

$$w_t = \chi C_t^{\sigma_C} L_t^{\zeta}. \tag{36}$$

Labor-market clearing equates L_t to labor demand from operating firms.

Foreign debt payments, the bank-capital transfer, and distributions to foreign owners imply net exports

$$NX_t = R^* \mathcal{F}_{t-1} - \mathcal{F}_t + \mathcal{X}_t + \Pi_t^B. \tag{37}$$

Let $\mathcal{L}_t$ denote total resources recovered from liquidated capital, $\mathcal{M}_t$ the mass of operating firms, and $\mathcal{E}_t$ the mass of entrants endowed with capital k_e. Aggregate resources satisfy

$$Y_t + \mathcal{L}_t = C_t + I_t + \Psi_t + F\mathcal{M}_t + k_e \mathcal{E}_t + NX_t. \tag{38}$$

Here Y_t includes the cash-flow endowments realized by operating firms, I_t is their investment, and Ψ_t collects both adjustment costs. Total liquidation resources are divided between creditor recoveries $\mathcal{L}_t^B$ and household receipts $\mathcal{L}_t^H$. Their definitions and the entry transfers are given in Appendix E.2.

3.6 Equilibrium

Given the initial distribution of firms, the inherited intermediary balance sheet, and the aggregate productivity and bank-transfer paths, an equilibrium consists of firm values and policies, debt prices, distributions $\{\mu_t\}$, and paths for wages, spreads, bank net worth, funding, consumption, and labor. Firms solve (17); debt prices satisfy (25); and firm distributions evolve under true transitions, optimal policies, default, exit, and entry. Intermediary returns and net worth satisfy (28) and (29), with credit clearing given by (32) in the binding regime and by (62) more generally. The household's budget and labor-supply conditions hold, labor markets clear, and aggregate resources satisfy (38).

A stationary equilibrium has $A = 1$, constant aggregate prices and quantities, and an invariant firm distribution. I compare the baseline model with a fundamentals-based pricing counterfactual in which $\eta_W = 0$. The two economies share firm technology, intermediary parameters, and household preferences. I calibrate χ to the baseline hours target described in Section 4.1. I keep χ fixed in the counterfactual, allowing its stationary wage, hours, consumption, and firm distribution to adjust. Appendix E.5 describes the stationary and transition calculations.

4 Quantitative Implementation and Validation

The model captures the share of bank credit held by high-risk firms outside the largest borrowers and the positive relation between the wedge and default two and three years ahead. Model and data also show larger loan-rate responses to assessments among smaller firms. Two differences matter for the counterfactuals: the model understates credit concentration among the largest borrowers, and its capital response to assessments is weaker. Every model firm already borrows, so changes in borrowing occur entirely among existing borrowers.

4.1 Measurement and Calibration

The model is annual. The calibration draws on firm accounts, rating gaps, and default histories. Appendix Tables B.1 and B.2 distinguish maintained assumptions, parameters informed by auxiliary estimates, parameters calibrated within the model, and quantities

derived from stationary conditions. Table 4.1 compares empirical and simulated moments; the remaining exhibits examine financial structure and financing responses.

Following Arellano, Bai, and Kehoe (2019), I set consumption curvature to $\sigma_C = 2$ and the inverse Frisch elasticity to $\zeta = 0.5$. The implied Frisch elasticity is 2. I calibrate χ so that average hours equal one in the baseline stationary equilibrium.

Productivity dynamics. Productivity persistence is $\rho_z = 0.74$, informed by a Nickell-corrected panel AR(1) estimate. The innovation standard deviation is $\sigma_z = 0.32$, informed by a separate AR(1)-plus-white-noise fit to two-year productivity autocovariances. The two values come from different auxiliary estimates.

Assessment persistence. The observed rating gap measures disagreement between two assessments and depends on the construction of the fundamentals-based rating. Its autocorrelation is therefore not a direct estimate of persistence in the model's assessment state. I set assessment persistence to $\rho_W \simeq 0.87$ (reported to two decimal places) unless otherwise stated. This choice is informed by an auxiliary AR(1)-plus-white-noise fit to the year-demeaned autocorrelation profile of an alternative, rated-firm-only, one-year rating-gap construction. The auxiliary fit does not separately identify measurement error and transitory assessment variation. The stationary mean wedge is set to $\mu_W = 0.19$; it is not an estimate of the sample mean.

Calibration evidence. The dispersion and within-firm variation of the rating gap inform the scale of assessment heterogeneity. Within-grade default differences inform η_W, the weight lenders put on assessments when forecasting productivity. The median and dispersion of leverage inform debt adjustment costs, while leverage persistence informs the maturing fraction γ. The mean investment rate informs capital adjustment costs, and the bankruptcy rate informs the fixed operating cost F. The exogenous exit probability π_x is informed by firm exits in the panel. These moments describe the main calibration evidence rather than separate one-moment estimates of each parameter. The required investment-financing share $\omega_I = 0.40$ is motivated by financing coverage in the firm accounts. Bank borrowing, including refinancing, covers 0.38 to 0.53 of positive investment; the model comparison gives 0.58 (Appendix Table B.3). This coverage ratio is an outcome of borrowing choices, rather than the financing requirement itself.

Financing prices. The empirical loan rate is interest expense over interest-bearing debt, an average over a firm's outstanding loans. The model's price is the quote on a new contract. Section 4.3 compares the magnitudes of their responses, allowing for this difference in measurement; the price response is not a calibration target.

Table 4.1: Empirical and Simulated Moments

Moment	Data	Model
Bankruptcy rate (%)	1.22	1.23
Median leverage	0.35	0.35
Leverage s.d.	0.36	0.29
Leverage autocorrelation	0.79	0.67
Mean investment rate	0.09	0.10
S.d. of W (grade-demeaned)	0.99	0.98
Within-firm s.d. of W	0.88	0.92
Within-grade default semi-elasticity	−0.88	−0.77

Notes: Bankruptcy is an annual percentage for all operating firms, dated at the firm's last filed accounts. Wedge moments use variation within agency grades. The last row is per fundamentals-based rating notch; its negative sign means default risk rises with the favorable wedge $W = R^A - R^F$. All entries are rounded to two decimal places. See Section 4.1 for sample definitions.

Default. Default rates differ by population and by how a failure is dated. The target is the bankruptcy rate of all operating firms, dated at the firm's last filed accounts: 1.22 percent a year, with other exits at 4.35 percent. Rated firms fail less often, 0.66 percent a year. Dating failures by the year of the bankruptcy filing instead counts only about a quarter of them (0.31 percent), because most bankrupt firms file their last accounts one to three years before the court opens the case. In the model, default is endogenous: a firm defaults when no feasible choice remains. Exogenous exit with probability π_x stands in for other exits.

4.2 Financial Structure and Risk Allocation

The results in Sections 5 and 6 depend on who holds credit and risk, which average leverage does not reveal. Table 4.2 compares the baseline model's stationary distribution with the data on three dimensions. Entries marked b use the fundamentals-based pricing counterfactual's distribution; the remaining model entries describe the baseline. The table notes specify the population used for each comparison.

Debt and firm size. Following Gertler and Gilchrist (1994), small firms are those that together account for the bottom 30 percent of sales. Outside the largest 1 percent of firms, they hold 31 percent of bank loans in the model and 24 percent in the data. Every model firm borrows, whereas only 29 percent of firm-years in the data have long-term bank loans. Firms with such loans account for about 32 percent of sales within both the small- and large-firm groups in the data. Small and large firms in the data carry about the same bank loans per unit of assets (a ratio of 0.99); in the model, small firms carry more (1.26). Size is total assets in the data and capital in the model, which has no other assets. The largest gap is at the top of the distribution. The largest 1 percent of firms

Table 4.2: Financial Structure: Model and Data

	Data	Baseline model
A. Debt and firm size		
Small firms' share of bank loans (%)	23.8	31.4
Bank loans per unit of assets, small relative to large firms	0.99	1.26[b]
Largest size quintile's share of bank debt (%)[a]	94	32.6
Largest 1% of firms' share of bank loans (%)[a]	50.1	2.2
B. Risk and economic activity		
High-risk firms' share of firms (%)	30.8	24.0[b]
High-risk firms' share of bank loans (%)	17.1	21.1
High-risk firms' share of capital (%)	13.2	13.5[b]
High-risk firms' share of investment (%)	–	7.2[b]
Large firms' bank debt with interest coverage below 2 (%)	36	8.3
C. Dynamics, default, and exit		
Autocorrelation of leverage	0.79	0.95
Default within three years (%)	2.54	2.94
lowest agency grade (%)	20.4	55.8
Default hazard on the wedge within grade, $h = 2$	0.94 (0.01)	1.55
Default hazard on the wedge within grade, $h = 3$	0.90 (0.01)	0.96
Exits for other reasons (% per year)	4.35	2.04

Notes: Norwegian operating firms and the model's stationary distribution. Bank loans in the data are long-term loans. Size is assets in the data and capital in the model. Small firms account for the bottom 30% of sales (Gertler and Gilchrist, 1994); large firms are the top size quintile. Loan-share, relative-leverage, firm-share, and capital-share rows exclude the largest 1%, except [a] rows. Investment shares and interest coverage use all sizes. The largest quintile's loan share uses the borrower sample in Section 2. High risk means fundamentals-based grade C in the data and a fundamentals-based loan spread of at least 250 basis points in the model. [b] Uses the fundamentals-based counterfactual's distribution; other model entries use the baseline. Interest coverage is earnings divided by interest payments. Leverage is liabilities over assets in the data and bank debt over capital in the model. Default-hazard entries are logit coefficients on the wedge h years ahead, with agency-grade and year effects; standard errors are in parentheses. – indicates an unreported statistic.

hold 2.2 percent of bank loans in the model and 50 percent in the data, and the largest size quintile holds 33 percent against 94 percent. Matching the size–leverage relation would not close this gap, because a group's share of loans also depends on how much of the economy's assets it holds. The model's size distribution is too compressed: the bottom 30 percent of sales outside the largest 1 percent comes from 85 percent of firms in the data and from about half of them in the model.

Risk and economic activity. High-risk firms are firms in shadow grade C in the data and, in the model, firms at states where the fundamentals-based contract would carry a spread of at least 250 basis points. Outside the largest borrowers they hold 17 percent of bank loans in the data and 21 percent in the baseline. In the fundamentals-based reference distribution, they hold 13.5 percent of capital, against 13.2 percent in the data, and account for 24 percent of firms, against 31 percent. Their investment share, measured over the full reference distribution, is 7.2 percent; the table reports no empirical counterpart for this share. Among large firms, the model understates risky debt: 8 percent of their bank debt has interest coverage below two, against 36 percent in the data.

Dynamics, default, and exit. Panel C reports dynamics, default, and exit. Leverage is more persistent in the model than in the data (0.95 against 0.79). The measures differ: the data use total liabilities over assets and the model uses bank debt over capital.

The three-year default rate is close (2.94 against 2.54 percent), but default is far more concentrated in the lowest agency grade (56 against 20 percent). Within an agency grade, firms with a more favorable wedge default more often two and three years later, as in the data: the logit coefficients are 1.55 and 0.96 in the model against 0.94 and 0.90. Exits for other reasons are less frequent in the model (2.0 against 4.4 percent a year).

Payouts and reported dividends measure different flows. Because the model has no liquid assets, payouts are the residual in the flow of funds (15) and include what a firm in the data would add to its cash holdings. Every model firm pays out each year; in the data, 16 percent of firm-years pay dividends.

The fit is stronger for credit allocation among small and mid-sized borrowers than for the largest borrowers, who hold about half of bank loans in the data. This concentration gap limits the model's account of aggregate bank credit.

4.3 Model-Implied Financing Responses

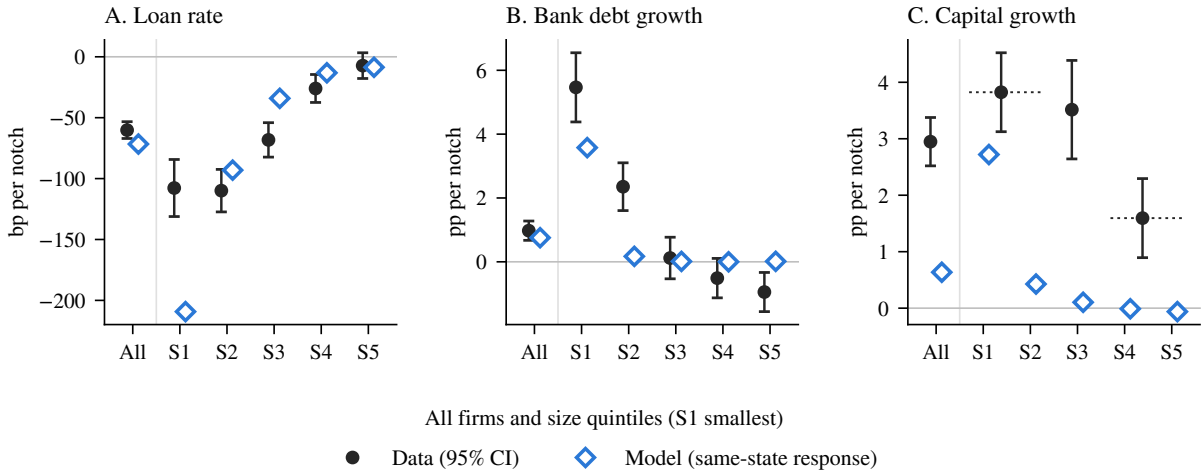
In both model and data, the loan-rate response is smaller in magnitude for larger firms. Borrowing responds along different margins: most of the empirical response among

small firms comes from firms that start to borrow, while all model firms already borrow. The model's capital response is also weaker, especially outside the smallest firms.

Section 2 estimates how a firm's loan rate, bank borrowing, and capital respond when its agency assessment improves relative to its fundamentals. Figure 4.1 sets these estimates beside the model's responses.

The model markers show the effect of raising a firm's assessment by one notch, from the mean of the assessment distribution to the next higher state, with all other firm states fixed. The empirical regressions instead condition on a fundamentals-based rating. The comparison therefore checks response magnitudes; comparing regression coefficients would require the empirical specification on simulated panels, as in Ottonello and Winberry (2020).

Figure 4.1: Financing Responses: Model and Data



Notes: Responses to a better assessment for all firms and by size quintile (S1 smallest; total assets in the data, capital in the model). Data: coefficients per notch of the wedge from the regressions in Section 2 (loan rate and bank debt growth: pooled specification; capital growth: the specification with the marginal product of capital), with 95 percent intervals. In Panel C the data group the two smallest and the two largest quintiles (dotted spans). Debt and capital growth are symmetric growth rates, in percentage points; the loan rate is in basis points. Model (hollow diamonds): the baseline's stationary policies with the firm's assessment raised by one notch, from the mean of the assessment distribution to the next higher assessment state, and all other state variables fixed; a same-state effect, not a regression on simulated data. $\mu_W = 0.19$.

A one-notch better assessment lowers the loan rate by 72 basis points across all firms in the model, against 60 basis points per notch in the data, and the response falls with size in both: 209 and 108 basis points in the smallest quintile, 9 and 7 in the largest. In the data, the rate of high-risk firms falls by 66 to 151 basis points in every size quintile, while the rate of other firms moves by at most 13 basis points. Part of the decline with size therefore reflects the mix of firms: high-risk firms are 57 percent of the smallest quintile and 9 percent of the largest. Part is a difference among high-risk firms themselves, whose response falls from 139 basis points in the smallest quintile to

70 in the largest. The model overstates the price response of the smallest firms by about a factor of two.

In the model and in the data, debt responds most in the smallest firms, but along different margins. Debt growth rises by 0.76 percentage points across all firms in the model and by 0.98 in the data, and by 3.6 and 5.5 points in the smallest quintile. Most of the data's small-firm response comes from firms that start to borrow. A better assessment raises the probability of starting to borrow by 2.5 percentage points in the smallest quintile; because a firm that starts to borrow has a symmetric growth rate of 200 percent, this margin accounts for 4.9 of the 5.5 points, and for almost all of the 2.4 points in the second quintile. In the smallest quintile, low-risk firms' loan rates do not fall, yet their debt grows as much as that of high-risk firms. These estimates come from separate price and borrowing regressions. Every model firm already borrows, and the assessment acts only through the loan rate, so the model's small-firm response comes from high-risk firms that borrow more when their rate falls.

The model's capital response is weaker than the empirical response. Capital growth rises by 0.64 percentage points in the model and by 2.95 in the data. Outside the smallest quintile the model's capital response is close to zero, while the data show 3.5 points in the middle quintile and 1.6 points in the two largest. The borrowing regressions show little response among these larger firms (Panel B), and their average loan rate falls by at most 68 basis points. Because the capital, borrowing, and loan-rate estimates use different specifications and samples, they do not identify how much of the capital response comes from cheaper bank credit. Other funding sources or information about fundamentals omitted from the regressions may contribute. The model allows internal funds but no external equity, and assessments do not alter the true productivity process. The comparisons do not distinguish these explanations.

Maturity is another margin outside the model. Large firms with low interest coverage respond to a better assessment by raising long-term bank debt by 1.26 percentage points of assets and reducing short-term bank debt by 1.93 points, with little change in total bank debt; a model with one debt instrument cannot produce this.

The counterfactuals use the model's mechanism for existing borrowers: assessments change debt prices and financing decisions, which shape the distribution of future credit risk.

5 Credit Assessments and the Allocation of Future Risk

Past assessments leave a loan book that carries more risk into a downturn. Under a common recession scenario, the baseline book suffers 4.5 percent more shock-added credit losses than the fundamentals-based counterfactual, while holding 0.9 percent

more credit. The loss difference is 0.79 basis points of the counterfactual's initial credit. Close to two-thirds comes from a larger share of lending to high-risk firms. This exposure also persists: after a one-notch over-rating, the assessment advantage halves within four years of the shift, while the additional losses under the common recession scenario take about two decades to halve from their peak.

The baseline model allows credit assessments to affect loan pricing. In the fundamentals-based pricing counterfactual, lenders price loans using the model-implied default risk without the assessment wedge ($\eta_W = 0$ in (23)). All other firm parameters are held fixed. The counterfactual retains default risk and the other financing frictions in the model. When I evaluate the stationary distributions of the two economies under a common pricing rule, I call them the baseline history and the fundamentals-based history.

The formation and assessment-shift experiments trace firms' financing choices at fixed aggregate prices. The recession tests evaluate the resulting distributions under common wage and lending-spread paths. The mean wedge is positive, $\mu_W = 0.19$. Appendix C repeats the formation and loss-decomposition experiments with $\rho_W = 0.5$.

5.1 The Formation of Credit-Risk Exposure

Both economies start from the same distribution of firms, the stationary distribution of the fundamentals-based counterfactual, and in year 0 lenders in one of them begin to price debt with credit assessments. Each firm draws an assessment from the baseline's stationary distribution of assessments, independently of its state. The new pricing regime treats some firms favorably and others unfavorably. Productivity, cash-flow shocks, exit, and entry follow the same processes in both economies. I trace how credit allocation evolves after the change in pricing, holding aggregate productivity and the common wage at their steady-state levels and each economy's lending spread at its own stationary value.

I track bank credit, its allocation across risk groups, and annual credit losses along this path. To measure the exposure accumulated through these financing choices, I subject the firm distributions at selected dates to the common recession scenario described in Section 5.2. For each distribution, exposure is the difference in cumulative credit losses over years 0 to 10 between the recession and corresponding no-shock paths. These tests are conducted separately and leave the formation path unchanged.

For firms issuing debt, a favorable assessment raises the funds obtained for a given face value. This financing benefit can help firms meet current obligations while allowing them to carry more debt into subsequent periods. Bank debt rises by 0.49 percent over 10 years and by 0.76 percent over 30 (Table 5.1, Panel A). Its long-run increase is 0.88 percent. The high-risk share of bank loans rises by 0.42 percentage points over 10 years

Table 5.1: Credit Accumulation and Exposure to a Common Recession

	Fundamentals-based benchmark	Assessment-based path		
		Year 0	Year 10	Year 30
A. Credit and annual losses without an aggregate shock				
Change in bank debt (%)	0.00	0.00	0.49	0.76
Change in high-risk credit share (pp)	0.00	0.00	0.42	0.62
Annual credit losses (bp)	62.72	59.91	61.38	62.25
B. Exposure to a common recession				
Cumulative shock-added losses (bp)	17.69	17.69	18.08	18.23

Notes. Years are measured from the start of assessment-based pricing. The benchmark is the stationary fundamentals-based economy. Panel A reports changes from year 0 in bank debt and the high-risk credit share, and annual losses in basis points of current credit. High-risk firms have a fundamentals-based loan spread of at least 250 basis points. Panel B reports cumulative recession losses minus losses on the same book's no-shock path over test years 0 to 10, in basis points of that book's initial credit. Both test paths use fundamentals-based pricing. Each distribution faces the same 5% TFP shock and the same recession paths for wages and the aggregate lending spread (Section 5.2). Credit losses are defaulted debt net of recoveries.

and by 0.62 over 30. Output stays within 0.03 percent of its starting level throughout. Appendix Figure C.3 shows the complete paths.

Each unit of credit carries more risk, and the losses that lenders realize in normal years do not reveal it. Under the common recession scenario, shock-added losses per unit of initial credit rise from 17.7 basis points at the start to 18.1 after 10 years and 18.2 after 30 (Panel B), 2.2 and 3.0 percent above the counterfactual. Losses in a year without a shock move the other way at first (Panel A). Assessment-based pricing, which is favorable on average because $\mu_W > 0$, lowers current defaults, so normal-year losses per unit of credit start 4.5 percent below the counterfactual's. They return to the counterfactual's level as credit shifts toward high-risk firms.

Combining the volume of credit and the risk per unit, total shock-added losses rise by 2.7 percent over 10 years and reach half of their long-run gap of 4.5 percent within 7 years. This experiment measures how exposure accumulates under a permanent change in pricing. Section 5.3 examines its persistence after a temporary assessment improvement. With a less persistent wedge, $\rho_W = 0.5$, credit grows more, by 1.2 percent over 30 years, but the risk per unit of credit grows more slowly, by 2.2 percent (Appendix Figure C.1).

5.2 Credit Quantity versus Risk Allocation

I subject the two stationary firm distributions to a common recession scenario to measure the exposure left by past financing choices. TFP falls by 5 percent and recovers as in (8). Both histories face the wage and aggregate lending-spread paths

from the fundamentals-based counterfactual's general-equilibrium recession. On the corresponding no-shock paths, these prices remain at the counterfactual's stationary values. Lenders use fundamentals-based pricing on both the recession and no-shock paths.

For a distribution of firms μ, shock-added credit losses are

$$\mathcal{E}(\mu) = \mathcal{L}^S(\mu) - \mathcal{L}^N(\mu), \tag{39}$$

where $\mathcal{L}^S(\mu)$ and $\mathcal{L}^N(\mu)$ are cumulative credit losses over years 0 to 10 on the recession and corresponding no-shock paths. Credit losses are defaulted face-value debt net of recoveries. Subtracting losses on the no-shock path separates exposure to the recession from differences in losses during normal times. Panel B of Table 5.1 reports shock-added losses per unit of each book's own initial credit. Table 5.2 uses the fundamentals-based book's initial credit as a common denominator when decomposing the difference in total losses.

I separate the long-run exposure gap into credit volume, allocation across risk groups, and loss rates within groups. The shock-added losses of a book can be written as

$$\mathcal{E} = B \sum_g s_g \ell_g + \mathcal{E}^{\text{ent}}, \qquad s_g = \frac{B_g}{B}, \qquad \ell_g = \frac{\mathcal{E}_g}{B_g}, \tag{40}$$

where B is total initial bank credit, s_g is the share of credit held by risk group g, ℓ_g is the group's shock-added losses per unit of its credit, and $\mathcal{E}^{\text{ent}}$ collects the losses of firms that enter after the onset of the recession. A difference in $\mathcal{E}$ between the two histories can therefore come from the volume of credit, its allocation across groups, loss rates within groups, or entrants. I replace credit volume first, then allocation, then within-group loss rates, moving each from the fundamentals-based history's value to the baseline's. Each step retains the earlier replacements, so interactions enter the later terms. Averaging over the six orderings changes no share by more than half a percentage point. Entrants enter as the difference in their own losses.

Risk groups are fixed by a common classification of the state, not by each economy's assessments. A firm is high risk if the contract that the fundamentals-based economy would choose at its state carries a spread of at least 250 basis points, about 60 basis points above what exogenous exit alone requires. The largest 1 percent of firms form a third group, and entrants are kept apart. The classification depends only on the state, so it does not move with assessments. Under the common recession scenario, both histories face the same pricing rule and the same paths of wages and the spread, so a firm in a given state has the same expected shock-added losses in either history. Differences in loss rates within a group therefore reflect which states within the group hold the credit, and how the difference splits between allocation and within-group loss rates depends

on how finely the groups are drawn. The decomposition is an accounting one. Firms move into high-risk states through their own financing and operating histories, so the allocation term includes transitions between states and differences in survival. It is not a transfer of loans between firms with fixed identities.

Table 5.2: Credit Allocation and Shock-Added Losses

A. Sources of additional losses

Source	Contribution (bp)	Share (%)
Credit volume	0.14	18
Allocation across risk groups	0.50	63
Within-group loss rates	0.13	16
Entrants	0.02	3
Total additional losses	0.79	100

B. Credit shares and loss rates by risk group

	Fundamentals-based history		Baseline history	
Risk group	Credit share (%)	Loss rate (bp)	Credit share (%)	Loss rate (bp)
High-risk firms	19.81	65.83	20.60	66.32
Low-risk firms	78.04	3.81	77.23	3.85
Largest 1% of firms	2.16	1.41	2.17	1.45

Notes. Both stationary histories face the same 5% TFP shock, fundamentals-based loan pricing, and wage and spread paths (Section 5.2). Shock-added losses are recession minus no-shock losses over years 0 to 10. Credit losses are defaulted face-value debt net of recoveries. Panel A decomposes the baseline history's additional losses, in basis points of the fundamentals-based history's initial credit. Credit volume, allocation, and within-group loss rates are replaced in that order. Entrants contribute their loss difference (Appendix Table C.2). In Panel B, high-risk firms have a fundamentals-based loan spread of at least 250 basis points. The largest 1% form a separate group. Loss rates divide each group's shock-added losses by its initial credit.

The modest increase in total credit masks a shift toward high-risk states. The baseline history carries 0.88 percent more credit than the fundamentals-based history, and high-risk firms hold 20.6 percent of it instead of 19.8 (Panel B). Under each economy's own pricing, losses in a normal year are the same per unit of credit, 62.7 basis points a year in both. Under the common recession scenario, shock-added losses are 18.48 basis points of the fundamentals-based history's initial credit in the baseline history and 17.69 in the fundamentals-based history. The difference is 0.79 basis points, or 4.5 percent. Per unit of each book's own initial credit, the difference is 3.5 percent. Appendix Table C.2 reports these levels.

A small change in loan shares matters because the groups differ sharply in losses per unit of credit. Under the common recession scenario, the high-risk group's shock-added losses are 66 basis points, seventeen times the low-risk group's 3.8 (Panel B). The allocation of credit across risk groups accounts for 0.50 of the 0.79 basis points, or 63 percent (Panel A). The volume of credit accounts for 0.14 (18 percent), higher loss rates

within risk groups for 0.13 (16 percent), and entrants for 0.02 (3 percent). Counted group by group, with contributions that add up to the total, the high-risk group accounts for 0.74 of the 0.79 basis points, or 94 percent (Appendix Table C.2). Its loss rate differs little across histories, at 66.3 basis points in the baseline and 65.8 in the counterfactual. Most of its additional losses come from the increase in credit held by the group.

For scale, the common recession scenario adds 17.7 basis points of initial credit to the fundamentals-based history's losses over eleven years. Normal-year losses are 63 basis points of credit per year.

The immediate borrowing response and the long-run debt gap have different distributions. In the same-state experiment of Figure 4.1, the smallest capital quintile accounts for 79 percent of the borrowing response but holds 4 percent of bank loans. Their small share of bank loans means that a large borrowing response need not translate into a large share of the additional debt in the long run. In the stationary comparison, high-risk states across size groups account for 111 percent of the net increase in debt. Lower debt in low-risk states offsets 11 percent of that increase (Appendix Figure C.2). A different distribution of firms across states accounts for 92 percent of the debt gap. Borrowing at a given state changes little. These comparisons describe responses and stationary stocks, without tracking individual firms between size and risk groups.

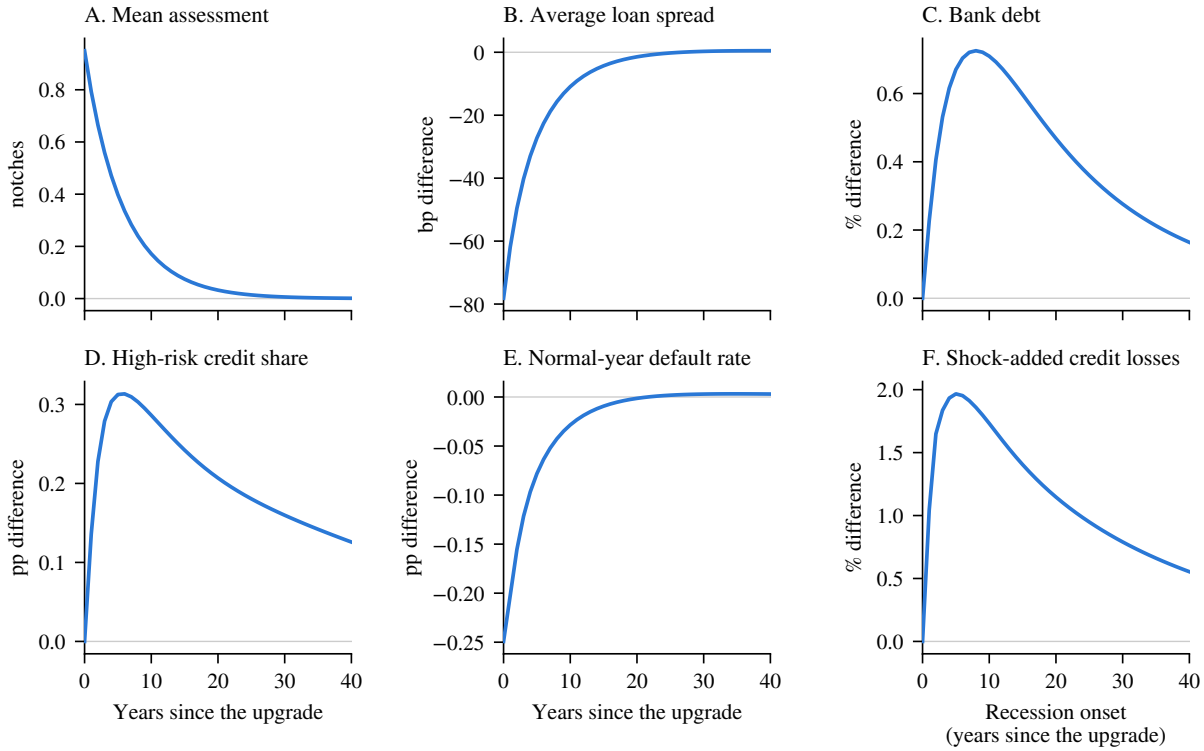
5.3 Risk after the Assessment Advantage Fades

Figure 5.1 traces the risk left behind by a temporary assessment improvement. At the start of year 0, every firm's assessment rises by one notch, subject to the upper bound, and the assessment process then runs as before. The over-rating fades according to (22), and entrants draw their assessments from the stationary distribution. Firms that already have the highest assessment keep it, so the mean assessment rises by 0.95 notches.

Wages and the aggregate lending spread remain at the baseline's stationary values along the paths with and without the assessment shift. Each panel reports the difference between these paths. Unlike the same-state comparison at the mean assessment in Figure 4.1, this experiment shifts assessments throughout the stationary distribution and follows firms' subsequent decisions. In the fundamentals-based pricing counterfactual the same shift changes nothing, because lenders there ignore assessments. Panel F evaluates each year's distribution under the common recession scenario of Section 5.2. Lenders price true risk from the onset of the recession, so the panel measures the risk carried by the balance sheets that the shift has built.

The mean assessment advantage falls by half within four years of the shift (Panel A). Loan spreads also recover quickly, but the borrowing they induce keeps rising after the initial financing advantage has begun to fade. Bank debt takes 17 years to halve from its

Figure 5.1: Credit Risk after the Assessment Advantage Fades



Notes. The baseline economy starts from its stationary distribution. At the start of year 0 every firm's assessment rises by one notch. Firms with the highest assessment keep it, so the mean rises by 0.95 notches. The assessment process then continues as before. Along the paths with and without the assessment shift, wages and the aggregate lending spread remain at the baseline's stationary values. The mean wedge is $\mu_W = 0.19$. Every panel shows the path with the shift minus the path without it. Panel A reports mean assessment in notches. Panel B reports the average spread on the loans firms choose, in basis points. Weighted by loans, the impact is −62 basis points and half of the impact gap closes within five years. Panel C reports bank debt in percent. Panel D reports the high-risk share of credit in percentage points. A firm is high risk if the fundamentals-based contract at its state carries a spread of at least 250 basis points. Panel E reports the default rate in a year without an aggregate shock, in percentage points. Panel F reports the difference in shock-added losses between the distributions with and without the assessment shift, evaluated under the common recession scenario of Section 5.2. Both distributions use fundamentals-based pricing on their recession and no-shock paths and face the same 5 percent TFP shock and aggregate price paths. The difference is expressed as a percentage of the shock-added losses of the book without the assessment shift. One percent equals 0.18 basis points of initial credit. In the fundamentals-based pricing counterfactual the same shift has no effect on any panel except A.

peak, and the additional shock-added losses take 19 years from theirs (Panels C and F). Appendix C reports the peak dates and the remaining timing measures.

Only a fraction of outstanding debt matures each period, and reducing the debt stock incurs adjustment costs. Firms can therefore continue to carry debt accumulated under favorable financing conditions as the assessment advantage fades. The contractual coupon and amortization rate remain fixed, while assessments can change the market value of outstanding debt, the proceeds from new issuance, and the cost of repurchases.

At its peak, the added exposure is 2.0 percent of the shock-added losses of the book without the assessment shift, or 0.36 basis points of initial credit. Defaults in normal years nevertheless remain below the path without the assessment shift for two decades (Panel E). Current default rates can therefore remain low while the loan book carries more exposure to a common recession.

Differences in credit-loss exposure need not imply proportionate differences in aggregate investment. The next section examines this distinction.

6 Aggregate Consequences

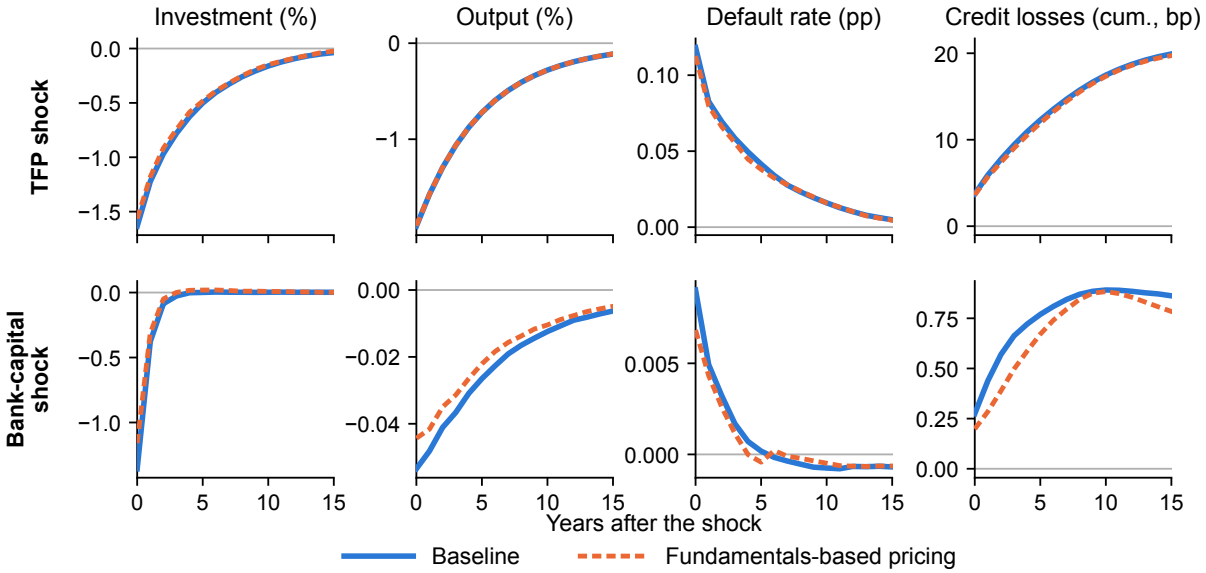
Section 5 shows that past credit assessments increase exposure to a common recession. I now examine how this vulnerability affects investment and output when each economy retains its pricing rule and aggregate prices adjust. The baseline's additional investment contraction is small after a TFP shock and larger after a bank-capital shock. Inherited financial positions explain little of the investment gap. Loan pricing during the downturn accounts for most of the additional contraction after the bank-capital shock.

6.1 Aggregate Responses to Adverse Shocks

Figure 6.1 compares the general-equilibrium responses to TFP and bank-capital shocks under the foreign-owned intermediaries described in Section 3.4. Each economy starts from its own stationary distribution and maintains its baseline pricing rule while wages, aggregate lending spreads, and firm decisions adjust endogenously. All responses are measured relative to each economy's no-shock path.

The bank-capital shock raises the required return on lending and tightens firms' financing conditions. Investment and output fall more significantly in the baseline, although aggregate lending-spread paths remain closely aligned across the two economies (Appendix Figure D.1). Over years 0 to 2, the baseline's cumulative investment decline is about 8 percent larger (Appendix Table D.1). The aggregate spread captures only part of a firm's financing conditions, as its debt price also depends on lenders' assessments of repayment prospects.

Figure 6.1: Aggregate Responses



Notes. General-equilibrium responses to a 5 percent TFP decline with persistence 0.8 (top row) and a 1 percent bank-asset write-down (bottom row). Each economy retains its pricing rule and is compared against its own no-shock path. Investment and output are 100 times log deviations, default rates are annual deviations in percentage points, and credit losses are cumulative deviations from year 0 in basis points of pre-shock fundamentals-based bank credit. Blue solid lines denote the baseline, and orange dashed lines denote fundamentals-based pricing. Appendix Figure D.1 reports wages, hours, capital, and the lending spread.

The TFP shock weakens earnings in both economies and produces smaller differences in their real responses. Over the same period, the baseline's cumulative investment decline is about 2.5 percent larger, while output responses exhibit little difference between the two economies. The stronger real amplification after the bank-capital shock persists even when the shocks are scaled to produce the same initial investment decline in the fundamentals-based economy (Appendix Table D.2). This investment and output comparison also holds against a counterfactual recalibrated to match the baseline default rate (Appendix Table D.3).

The baseline exhibits default amplification after both shocks, but the relative increase is smaller following the TFP shock than following the bank-capital shock. Nonetheless, its cumulative credit losses over years 0 to 10 are lower after both shocks (Figure 6.1 and Appendix Table D.1). Annual default rates and cumulative losses cover different horizons and weight borrowers differently. Credit losses depend on the debt and recoveries of defaulting firms, whereas aggregate investment depends on capital spending across the firm distribution. Firms responsible for a large share of credit losses may undertake little investment, and likewise, borrowers can cut investment without defaulting.

I next examine which firms account for the investment gap and whether it stems from inherited financial positions or loan pricing during the downturn.

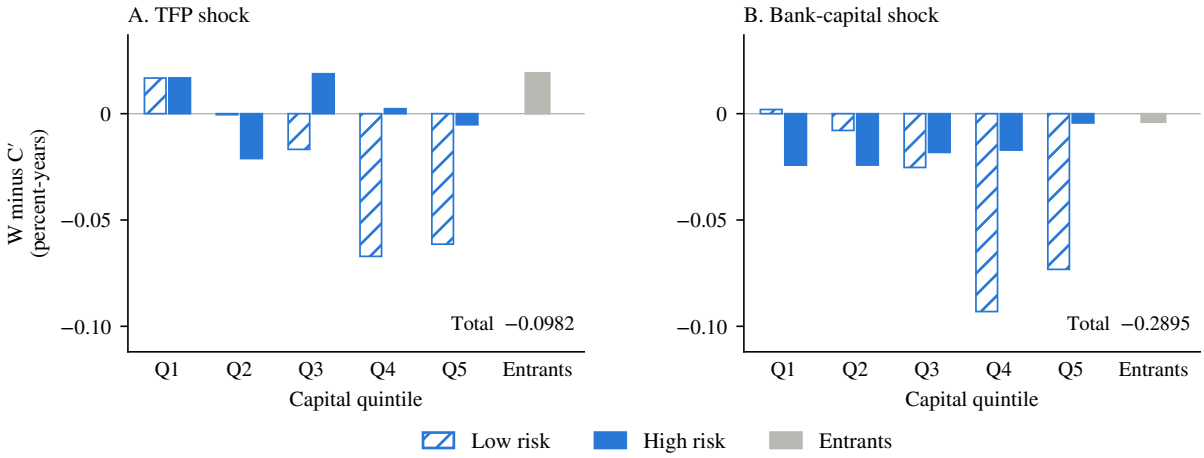
6.2 Firm Heterogeneity

Low-risk firms in the two largest capital quintiles account for most of the additional investment decline in the baseline after both shocks. By contrast, the contribution of high-risk firms differs across shocks: they narrow the investment gap after the TFP shock but widen it after the bank-capital shock.

I decompose the general-equilibrium responses of Section 6.1 by firms' pre-shock risk and capital. Both the baseline and the fundamentals-based counterfactual use a common risk classification and common capital cutoffs, with initial firms remaining fixed in their assigned groups throughout the transition. Each economy starts from its own stationary distribution and retains its pricing rule as wages and the lending spread adjust, while entrants are tracked separately and included in the aggregate. Contributions measure the baseline minus the counterfactual investment response, cumulated over years 0 to 10.

After the TFP shock, low-risk firms in the fourth and fifth capital quintiles contribute −0.128 percent-years to the aggregate investment gap (Figure 6.2), reflecting the fact that these firms undertake 53.4 percent of normal investment (Table 6.1). Among low-risk firms in the fourth quintile, cumulative investment falls by 4.69 percent of normal annual investment in the baseline, compared with 4.40 percent in the counterfactual. Although the difference is modest, this group accounts for nearly one-quarter of aggregate investment. Its contribution illustrates how investment weights translate modest differences in firm-level responses into large aggregate effects, as in the aggregation analysis of Crouzet and Mehrotra (2020).

Figure 6.2: Investment Contributions



Notes. Contributions to the baseline minus fundamentals-based investment response over years 0–10, in percent-years (cumulative percentage deviations). Groups are fixed by pre-shock risk and capital. High-risk firms have a fundamentals-based reference spread of at least 250.1 basis points. Capital quintiles use common baseline cutoffs, from Q1 (smallest) to Q5 (largest). Blue, hatched, and gray bars denote high-risk firms, low-risk firms, and entrants. Negative values indicate a deeper contraction in the baseline.

High-risk firms narrow the gap after the TFP shock, contributing +0.012 percent-years. Among high-risk firms in the smallest capital quintile, cumulative investment falls by 50.8 percent of normal annual investment in the baseline and 54.8 percent in the counterfactual. These firms therefore contract sharply under both pricing rules, albeit with a smaller decline in the baseline. Their strong response to the downturn does not imply a larger contraction in the baseline. Moreover, high-risk firms undertake little normal investment, although they can matter more for credit losses, which depend on the debt of defaulting firms. Taken together, contributions outside the two largest low-risk groups narrow the net investment gap to −0.098 percent-years.

Table 6.1: Investment Weights and Contributions

Firm group	Investment share (%)	TFP shock	Bank-capital shock
Low-risk initial firms	93.85	−0.129	−0.197
Of which Q4 and Q5	53.44	−0.128	−0.166
High-risk initial firms	6.15	+0.012	−0.088
Entrants	—	+0.019	−0.004
All firms	100.00	−0.098	−0.290

Notes. Investment shares use the fundamentals-based stationary distribution. Contributions follow Figure 6.2 and are measured in percent-years. Q4 and Q5 are included in low-risk initial firms. Entrants have no initial investment share. Totals use unrounded values.

In contrast, after the bank-capital shock, high-risk firms contribute to the additional contraction in every capital quintile. They account for 30.4 percent of the investment gap despite undertaking only 6.2 percent of normal investment. Their contribution is therefore sizable relative to their investment weight, whereas under the TFP shock their responses narrow the gap. Low-risk firms in the fourth and fifth quintiles still account for 57.4 percent of the gap. Thus, most of the additional decline remains concentrated among large low-risk firms, while high-risk firms now deepen the contraction as well. Entrants account for a negligible share of the gap.

These group comparisons leave open how much of the investment gap stems from inherited financial positions versus current loan pricing.

6.3 Inherited Debt

The inherited firm distribution raises credit losses under both shocks but contributes little to the investment gap. Current loan pricing accounts for most of the additional investment contraction in the decomposition, especially after the bank-capital shock.

To quantify the role of past financing choices, I compare the stationary distributions underlying Section 6.1 under fundamentals-based pricing and common aggregate price paths, as in Section 5.2. These distributions differ in the debt, capital, and productivity

of firms entering the downturn. The inherited component captures the joint effect of these state differences, which reflect past borrowing, investment, and survival.

Let $\mathcal{R}_{hr}(\Pi)$ denote the cumulative response over years 0 to 10 for history h, pricing rule r, and aggregate price paths Π. The subscripts b and f denote the baseline and fundamentals-based economies. Each response is measured against a no-shock path with the same initial distribution and pricing rule. Each Π contains the corresponding shock and no-shock price paths.

Starting from the fundamentals-based economy, I first replace the initial distribution, then change the pricing rule, and finally replace the aggregate price paths. The difference between the two general-equilibrium responses is

$$\begin{aligned}\mathcal{R}_{bb}(\Pi_b) - \mathcal{R}_{ff}(\Pi_f) = {} & \underbrace{\mathcal{R}_{bf}(\Pi_f) - \mathcal{R}_{ff}(\Pi_f)}_{\text{Inherited distribution}} \\ & + \underbrace{\mathcal{R}_{bb}(\Pi_f) - \mathcal{R}_{bf}(\Pi_f)}_{\text{Current pricing}} \\ & + \underbrace{\mathcal{R}_{bb}(\Pi_b) - \mathcal{R}_{bb}(\Pi_f)}_{\text{GE feedback}}.\end{aligned} \tag{41}$$

The first two components use the fundamentals-based economy's equilibrium wage and lending-spread paths, with stationary prices for their no-shock counterparts. The GE component switches to the corresponding baseline paths. All experiments include initial firms and entrants, so the components sum to the general-equilibrium difference in Section 6.1. The decomposition is sequential: the interaction between history and pricing is assigned to the current-pricing component.

Table 6.2: Response Decomposition

Outcome	Inherited	Current pricing	GE	Total
A. TFP shock				
Credit losses (bp)	+0.6349	−0.7487	−0.0254	−0.1392
Investment (percent-years)	−0.0191	−0.0642	−0.0148	−0.0982
B. Bank-capital shock				
Credit losses (bp)	+0.0457	−0.0819	−0.0514	−0.0876
Investment (percent-years)	+0.0120	−0.3589	+0.0573	−0.2895

Notes. Cumulative contributions over years 0–10 to the baseline minus fundamentals-based response, as defined in (41). Shocks are a 5 percent TFP decline and a 1 percent bank-asset write-down. Credit losses are in basis points of fundamentals-based initial credit. Investment sums 100 times the log ratio of shock to no-shock investment, in percent-years. Negative investment values indicate a deeper contraction. Totals use unrounded components.

Two features of the common-price TFP experiment explain the small investment effect. First, high-risk initial firms account for about 92 percent of additional credit losses but only 6.2 percent of normal investment. Losses depend on debt exposed to default, giving these borrowers a different weight from their share of capital spending. Second, these firms already cut investment sharply under fundamentals-based pricing. Changing the financing history deepens their cumulative investment decline by only about 2.2 percent. The inherited effect is therefore limited by both their small investment weight and the modest change in their response.

To quantify the role of investment weights, I reweight the group responses while holding those responses and aggregate prices fixed (Appendix Table D.5). The exercise uses investment changes in levels. Giving high-risk firms an investment weight equal to their share of additional losses increases the investment contraction attributable to inherited states. Assigning all investment to them adds little further because changing the history has only a modest effect on their own investment response.

Changing the pricing rule produces a different pattern. After the TFP shock, assessment-based pricing reduces defaults and lowers the credit-loss response by 0.7487 basis points relative to fundamentals-based pricing. Investment nevertheless falls by more, with a contribution of -0.0642 percent-years to the aggregate gap. Lower defaults and credit losses therefore do not imply a smaller aggregate investment contraction.

After the bank-capital shock, current pricing contributes -0.3589 percent-years to the investment gap, compared with a total gap of -0.2895 percent-years. Equilibrium price adjustment contributes $+0.0573$ percent-years, reducing the additional contraction. Current pricing also lowers the total credit-loss response, but the decline comes from entrants. The pricing component raises the loss response among initial firms, while reducing the entrant loss response by a larger amount.

6.4 Banking and Pricing

Assessment-based pricing cushions the funding response of high-risk firms with above-mean assessments after the TFP shock, but deepens their funding decline after the bank-capital shock. Among low-risk firms, investment responses also depend on continuation values and debt-price levels, so changes in current funding alone do not explain their adjustment.

I use the current-pricing comparison from Section 6.3. The baseline history is held fixed, and both pricing rules face the fundamentals-based economy's wage and lending-spread paths. Each response subtracts the corresponding no-shock path under the same pricing rule.

Figure 6.3 compares financing on fixed contracts with investment after firms re-optimize, connecting financing conditions to firm adjustment as in Ottonello and

Winberry (2020). The reference contracts are those chosen under fundamentals-based pricing without the shock, evaluated at the same firm states. Holding these contracts fixed, funding changes equal debt-price changes times net issuance. The investment responses allow firms to choose borrowing and investment under each pricing rule.

High-risk firms with above-mean assessments show the clearest difference across shocks. After the TFP shock, their reference contracts lose less funding and their investment falls less under assessment-based pricing. After the bank-capital shock, both responses are more negative. High-risk firms with below-mean assessments display the opposite pattern.

These results are consistent with different roles for repayment expectations and discounting. A TFP shock weakens repayment prospects. An optimistic assessment can limit the deterioration perceived by lenders and reduce the fall in debt prices. A bank-capital shock instead raises the required return on lending. If a favorable assessment makes lenders expect payments to continue for longer, the higher discount rate can produce a larger decline in the debt price. Contractual coupons and amortization rates remain fixed.

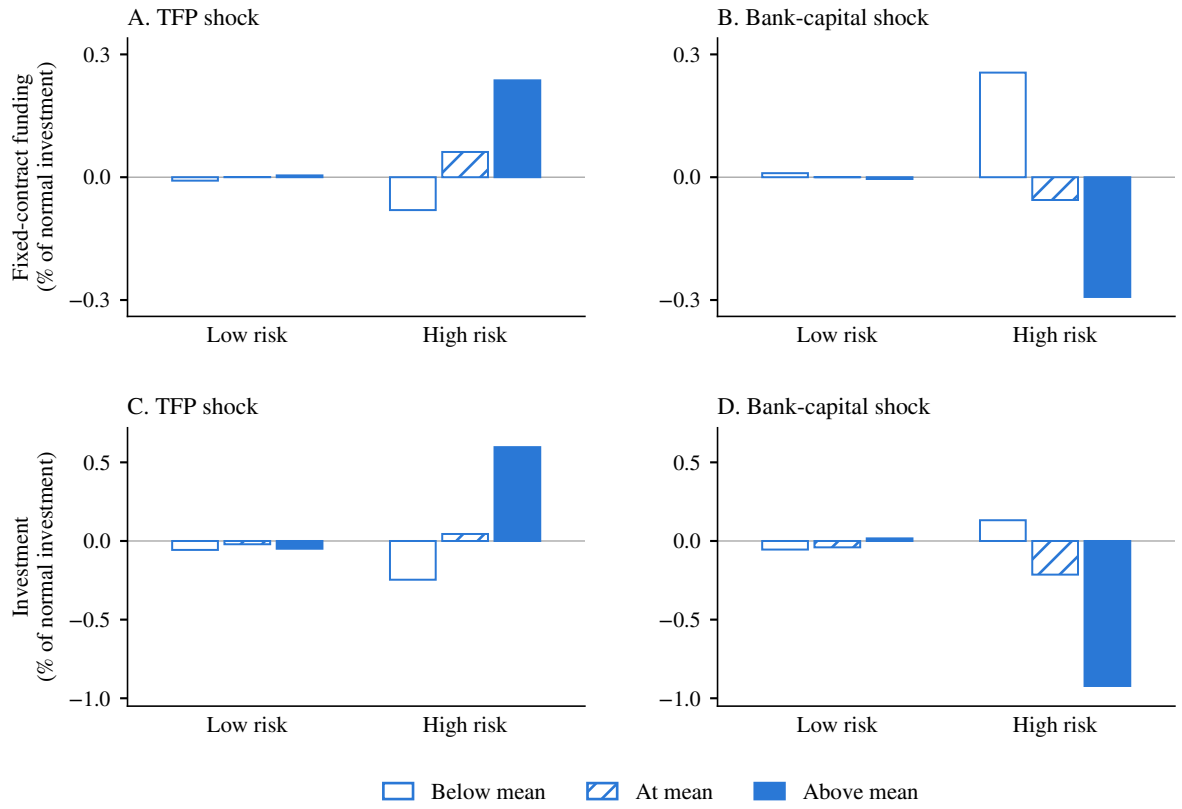
The average funding response conceals differences within the low-risk, above-mean assessment group. After the TFP shock, about 6 percent of these firms face a worse funding response on their reference contracts. They account for roughly two-thirds of the group's additional investment decline. Investment also falls more among the remaining firms, even though their reference contracts receive financing support.

To understand the response of these remaining firms, I change current debt-price schedules and continuation values separately in a one-period calculation. Changes in continuation values account for most of their additional investment decline. Their choices therefore depend on the value of future capital and debt positions as well as current financing. For the low-risk, above-mean assessment group as a whole, capital spending and adjustment costs fall more, while payouts fall less and debt service changes little. The group's investment is already slightly lower under assessment-based pricing on the no-shock path, and the gap widens during the recession.

After the bank-capital shock, low-risk firms with below-mean assessments lose slightly less funding on their reference contracts under assessment-based pricing. Those contracts, however, have lower prices even without the shock. The probability that they become infeasible rises by an additional 0.66 percentage points. Firms can choose alternative contracts, and investment falls more while actual defaults change little. The one-period calculation attributes most of this group's additional investment decline to changes in current debt-price schedules. It does not separately identify how much of this effect operates through the financing constraint.

Appendix Table D.6 reports how these responses accumulate over years 0 to 10. After the TFP shock, low-risk initial firms deepen the investment decline, while high-risk firms

Figure 6.3: Financing Conditions



Notes. Impact responses under assessment-based minus fundamentals-based pricing, using the baseline history and common fundamentals-based wage and lending-spread paths. Each response subtracts its own no-shock path. Columns show a 5 percent TFP decline and a 1 percent bank-asset write-down. Upper panels report debt-price changes times net issuance on fixed reference contracts; lower panels report investment after re-optimization. Reference contracts and weights follow the fundamentals-based no-shock policy. Both measures are percentages of each group's date-0 fundamentals-based no-shock investment.
High-risk firms have a fundamentals-based reference spread of at least 250.1 basis points. Outlined, hatched, and solid blue bars denote assessments below, at, and above the mean of 0.19. Funding covers states with a reference contract; investment covers all states in the group.

with mean or above-mean assessments reduce it. After the bank-capital shock, low-risk initial firms account for about 71 percent of the current-pricing effect. Their large investment weight makes even modest response differences important for the aggregate. Under this shock, low-risk firms with above-mean assessments also contribute to the cumulative decline, although their investment falls less on impact.

The GE component in Table 6.2 combines changes in wages and lending spreads. Quantifying the separate feedback from firm loan losses through bank net worth would require a counterfactual that removes this feedback while retaining the original aggregate shock.

7 Conclusion

In this paper, I study how lenders' credit assessments shape firms' vulnerability to future downturns. Using Norwegian firm-level data, I show that financial fundamentals predict bankruptcy even within the same external credit rating. Among firms with similar fundamental risk, more favorable external ratings lead to lower borrowing costs and different financing choices. To quantify these mechanisms, I build a heterogeneous-firm model. In the model, firms make decisions based on true productivity, while banks price debt using forecasts distorted by credit assessments. These assessments therefore change corporate borrowing and investment through financing terms, without directly affecting firm productivity.

The model shows that credit risk can build up quietly even when total credit barely changes. In the long run, assessment-based pricing raises total credit by only 0.9 percent compared to a fundamentals-based benchmark. Yet under the same recession shock, credit losses are 4.5 percent higher. Roughly two-thirds of this increase comes from risk shifting toward riskier firms, rather than higher total debt. Because debt and capital adjust slowly, favorable assessments tilt loan portfolios toward riskier borrowers. This creates exposures that outlast the initial financing advantage.

However, whether these accumulated risks hurt aggregate investment depends heavily on the source of the crisis shock. Under a productivity shock, the additional drop in aggregate investment is small because the high-risk firms driving most credit losses account for only a tiny share of total investment. By contrast, under a bank capital shock, decomposing the general equilibrium effects shows that most of the extra investment drop comes from tighter credit pricing during the downturn, rather than pre-crisis debt levels. Specifically, this pricing channel hits financially sound firms that account for most aggregate investment. Thus, while past borrowing shapes the vulnerabilities firms carry into a crisis, the real-economy damage depends on how a given shock transmits through current credit pricing to major investing firms.

The findings yield two key implications for financial risk monitoring and the design of stress-test scenarios. First, distortions in credit assessments can alter the allocation of risk even under modest aggregate credit growth, creating structural exposures that outlast the favorable assessments that generated them. Second, the real-economy effects of this friction depend heavily on the nature of the shock: quantitative experiments show that the friction amplifies investment contractions significantly more under a bank capital shock than under a productivity shock, driven primarily by post-shock adjustments in credit pricing.

Consequently, financial stability surveillance must account for both the accumulation of risks in loan portfolios during booms and the heterogeneous transmission of crisis shocks to corporate financing and investment. Regulatory stress tests should explicitly

compare scenarios driven by deteriorating corporate profitability against those involving impaired bank funding capacity. In doing so, particular attention should be directed toward firms that drive a large share of real investment, even when their individual default risk appears low. This study provides a rigorous quantitative framework for identifying these structural vulnerabilities and assessing their transmission to the real economy across diverse stress scenarios.

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A Empirical Appendix

A.1 Construction of the Measurement and Financing Samples

The starting accounting panel contains AS and ASA firms with positive assets and at least two observations in the panel. It excludes observations with negative revenue and firms in industry code 8. In 2008–2017, this panel contains 2,197,979 firm-years. I remove 20 observations with missing rating codes, 89,247 with code 9 and 31,203 with other codes outside the standard agency scale of C, B, A, AA and AAA. Excluding a further 4,260 observations in or after the firm's bankruptcy year leaves the measurement sample of 2,073,249 firm-years from 346,251 firms.

The financing sample starts from these measurement firm-years. Requiring complete current-year controls leaves 2,066,374 observations, of which 1,036,020 have an observed borrowing cost at $t + 1$. This outcome requires interest-bearing debt at $t + 1$. Requiring admissible next-year long-term bank-loan balances removes 163 observations, and recursive removal of singletons for firm, fundamentals-based-rating-by-year and industry-by-year effects removes 38,057, leaving 997,800 firm-years. I then exclude 759 observations with negative or missing bank or bond balances in either year and the 52 singletons this creates. The final financing sample contains 996,989 firm-years from 172,489 firms, or 48.1 percent of the measurement firm-years. Appendix A.5 defines the financing variables.

The financing sample contains larger firms and a higher share of bank or bond borrowers (Table A.1). Median assets are NOK 4.88 million, compared with NOK 2.70 million in the measurement sample. The share without bank or bond debt is 42.4 percent, compared with 68.4 percent. These statistics describe accounts at t and give each firm-year equal weight. Firms with no interest-bearing debt at t remain eligible because the borrowing-cost requirement applies at $t + 1$.

Table A.2 extends the main summary table to debt service, growth, employment and the additional accounting ratios used in the financing regressions. Table A.3 reports standard deviations and available observation counts within each agency rating. Both use observed accounting quantities, before the winsorization, standardization and imputation used in estimation. Interest-bearing debt is reconstructed from its reported components, keeping missing components missing. Negative balances are excluded from the relevant stock measure, while negative operating profit remains valid. Ratios require positive denominators. Large standard deviations, particularly for leverage, interest-bearing debt and growth, reflect long tails in these untrimmed distributions.

Table A.1: Measurement Sample and Final Financing Sample

	Measurement	Financing
Firm-years	2,073,249	996,989
Firms	346,251	172,489
C share (%)	3.2	2.9
B share (%)	19.7	23.4
A share (%)	39.1	33.2
AA+ share (%)	38.1	40.5
Median assets (NOK m)	2.70	4.88
Median age (years)	7.0	8.0
Mean leverage	4.128	4.575
Mean operating ROA	-0.213	-0.114
Mean cash / assets	0.260	0.149
Mean interest-bearing debt / assets	2.266	3.284
Mean bank and bond debt / assets	0.373	0.521
No interest-bearing debt (%)	48.0	8.0
No bank or bond debt (%)	68.4	42.4
Has a long-term bank loan (%)	26.6	49.5
Available observations for financial characteristics		
Leverage	2,069,079	996,989
Operating ROA	2,073,249	996,989
Cash / assets	2,067,671	993,750
Interest-bearing debt / assets	2,068,619	996,344
Bank and bond debt / assets	2,070,301	996,989
Long-term bank loans / assets	2,072,694	996,989

Notes: Current-year accounts, 2008–2017. The financing sample is the regression sample in Table 2.3. Firm-years receive equal weight; statistics use observed values for each variable before imputation, winsorization or standardization. Assets are in nominal NOK million; ratios are fractions. Rating shares use the sample in each column; zero-debt and loan-participation shares use the corresponding variable counts. Zero-debt shares require complete, nonnegative debt components. The borrowing-cost requirement applies to interest-bearing debt at $t + 1$. Variable definitions and cleaning follow Table A.2.

Table A.2: Financial Characteristics in the Measurement Sample

Variable	*N*	Mean	SD	P10	Median	P90
Total assets (NOK m)	2,073,249	47.11	1,891.09	0.17	2.70	31.09
Firm age (years)	2,073,249	10.6	12.4	1.0	7.0	24.0
Leverage	2,069,079	4.128	285.818	0.039	0.645	1.110
Operating ROA	2,073,249	-0.213	27.382	-0.194	0.009	0.296
Cash / assets	2,067,671	0.260	0.322	0.001	0.128	0.763
Interest-bearing debt / assets	2,068,619	2.266	126.640	0.000	0.019	0.859
Bank and bond debt / assets	2,070,301	0.373	42.416	0.000	0.000	0.597
Employees	1,845,654	7.1	79.0	0.0	1.0	12.0
Interest coverage	1,083,534	89.930	1,669.442	-14.818	1.772	142.000
Asset growth	1,879,355	7.584	1,126.354	-0.294	0.006	0.660
Short-term share of liabilities	1,990,151	0.688	0.405	0.034	0.971	1.000
Tangible assets / assets	2,073,086	0.220	0.338	0.000	0.020	0.860
Revenue / assets	2,073,249	1.519	20.831	0.000	0.323	3.474
Cash earnings / assets	2,073,249	-0.183	27.343	-0.162	0.028	0.331
Long-term bank loans / assets	2,072,694	0.241	30.388	0.000	0.000	0.537
Short-term bank loans / assets	2,070,895	0.070	9.711	0.000	0.000	0.000
Long-term share of bank loans	648,271	0.798	0.374	0.000	1.000	1.000
No liabilities (indicator)	2,066,176	0.037	0.188	0.000	0.000	0.000
No bank loans (indicator)	2,070,348	0.687	0.464	0.000	1.000	1.000

Notes: The sample contains 2,073,249 firm-years in 2008–2017. Firm-years receive equal weight; statistics use observed values before imputation, winsorization or standardization. *N* varies by variable. Negative age, employment and accounting stocks are treated as missing; negative operating profit is retained. Assets are in nominal NOK million; ratios are fractions with positive denominators. Leverage and operating ROA are liabilities and operating profit divided by assets. Interest-bearing debt combines long-term interest-bearing liabilities with the midpoint of the reported short-term bounds. Bank and bond debt sums short- and long-term bank loans and bonds. Debt measures require all components to be observed and nonnegative. Interest coverage divides operating profit by interest expense net of interest paid to group companies, with both expense components observed. Asset growth uses consecutive eligible accounts. Cash earnings are operating profit plus depreciation. Bank-loan measures exclude bonds. Indicators equal one when the stated condition holds and zero otherwise.

Table A.3: Within-Rating Dispersion and Variable Coverage

	All	C	B	A	AA+
Panel A: Standard deviations within rating categories					
Total assets (NOK m)	1,891.09	92.47	209.52	1,152.74	2,829.44
Firm age (years)	12.4	8.7	10.7	11.2	13.7
Leverage	285.818	382.554	625.079	5.197	12.142
Operating ROA	27.382	61.599	56.309	2.270	2.254
Cash / assets	0.322	0.333	0.393	0.327	0.267
Interest-bearing debt / assets	126.640	327.278	252.469	4.328	11.833
Bank and bond debt / assets	42.416	133.589	78.939	0.792	0.219
Panel B: Nonmissing observations within rating categories					
Total assets (NOK m)	2,073,249	66,884	407,456	809,766	789,143
Firm age (years)	2,073,249	66,884	407,456	809,766	789,143
Leverage	2,069,079	66,644	407,056	806,852	788,527
Operating ROA	2,073,249	66,884	407,456	809,766	789,143
Cash / assets	2,067,671	65,977	405,292	808,264	788,138
Interest-bearing debt / assets	2,068,619	66,489	406,326	808,266	787,538
Bank and bond debt / assets	2,070,301	66,653	406,669	808,913	788,066
Long-term bank loans / assets	2,072,694	66,800	407,329	809,574	788,991

Notes: The measurement sample covers 2008–2017; AA+ combines AA and AAA. Firm-years receive equal weight. Statistics use observed accounting values, without imputation, winsorization or standardization. Assets are in nominal NOK million; ratios are fractions. Standard deviations use $N - 1$ in the denominator. Debt counts give the denominators for the corresponding zero-debt and loan-participation shares in Table 2.1. Bankruptcy rates in that table use all firm-years in each column. Table A.2 gives variable definitions and cleaning rules.

A.2 The Information Test

I estimate the linear probability model in equation (1) with next-year bankruptcy as the outcome and agency-rating-by-year effects. The eight predictors are leverage, operating ROA, interest coverage, cash over assets, log assets, firm age, asset growth and the short-term share of liabilities. Firm age is the accounting year minus the year of establishment. Table A.2 defines the accounting ratios.

The baseline uses firm-years with all eight predictors observed. This leaves 1,019,223 firm-years from 222,128 firms, with 214 bankruptcies in the following year. Each year, I clip the predictors at the 1st and 99th percentiles and standardize them using rated firm-years from 2005 through $t - 2$.

In the measurement sample, interest coverage is missing in 47.7 percent of firm-years, asset growth in 9.4 percent and the short-term liability share in 4.1 percent. Table A.4 reports the baseline in column (1) and the estimates with AA and AAA treated separately in column (2). Both columns use the same complete-case sample.

Table A.5 adds six other accounting variables and then six measures of debt structure and borrowing cost. All three columns use the same complete-case sample of 508,922 firm-years from 116,544 firms in 2008–2017, with 100 bankruptcies in the following year. The eight original characteristics remain jointly significant in every column ($p < 0.05$).

A.3 Fundamentals-Based Ratings and Rating Disagreement

A.3.1 Construction of the Fundamentals-Based Rating

Prediction model. I predict next-year bankruptcy with a histogram-based gradient-boosting classifier, using the eighteen inputs described in Section 2.3. The agency rating is not a predictor.

For each prediction year t, I use eligible accounts from 1999 through $t - 1$, including firms without a standard agency rating. I divide these historical account years into two periods. The earlier years are used to fit the model. The most recent 20 percent of account years are reserved for calibration, rounding down to whole years with a minimum of one year.

When fitting the model, I give bankruptcy observations greater weight because they are rare. I then use isotonic regression on the calibration sample to map model scores to observed bankruptcy frequencies while preserving their risk ordering. Applying the calibrated model to year-t accounts gives the predicted probability of bankruptcy in $t + 1$.

For example, predictions based on 2017 accounts use a model fitted on 1999 to 2013 accounts and calibrated on 2014 to 2016 accounts. The calibration outcomes are bankruptcies in 2015 to 2017. I then apply the model to 2017 accounts to predict

Table A.4: Do Firm Characteristics Predict Bankruptcy within Agency Ratings?

	Four agency ratings (1)	Five agency ratings (2)
Leverage	1.588	1.588
	(0.500)	(0.500)
Operating ROA	−0.291	−0.292
	(0.410)	(0.410)
Interest coverage	0.073	0.075
	(0.097)	(0.097)
Cash / assets	−0.224	−0.225
	(0.230)	(0.231)
Log assets	−0.316	−0.317
	(0.168)	(0.168)
Firm age	−0.267	−0.267
	(0.127)	(0.127)
Asset growth	−0.034	−0.034
	(0.191)	(0.191)
Short-term liability share	0.689	0.690
	(0.141)	(0.141)
Firm-years	1,019,223	1,019,223
Firms	222,128	222,128
Events	214	214
Agency ratings	4	5
Rating × year effects	Yes	Yes
Clustering	Firm	Firm
R^2	0.001094	0.001097
Wald $\chi^2(8)$	50.55	50.60
Joint p-value	3.21×10^{-8}	3.14×10^{-8}

Notes: Column (1) reports the baseline linear probability model in equation (1). The outcome is formal bankruptcy in $t + 1$. Both columns use firm-years with all eight characteristics observed. Column (1) pools AA and AAA into AA+. Column (2) retains five agency ratings. Each agency-rating-by-year combination has a separate intercept. The table reports the coefficients on firm characteristics. Firm age is the accounting year minus the year of establishment. Coefficients and standard errors are in basis points per historical standard deviation of the characteristic. The Wald test is for the eight characteristics. Standard errors clustered by firm in parentheses.

Table A.5: Financial Characteristics and Bankruptcy with Additional Controls

	(1)	(2)	(3)
Eight financial characteristics	Yes	Yes	Yes
Other accounting controls	0	6	6
Debt and cost controls	0	0	6
Rating × year effects	Yes	Yes	Yes
Firm-years	508,922	508,922	508,922
Firms	116,544	116,544	116,544
Bankruptcies	100	100	100
R^2	0.001734	0.001741	0.001779
Wald $\chi^2(8)$	52.28	20.95	18.25
Joint p-value	1.48×10^{-8}	0.00727	0.01942

Notes: Linear probability models of bankruptcy in $t + 1$, with the eight characteristics in equation (1). All columns use the same firm-years in 2008–2017 with every variable in column (3) observed. Agency-rating-by-year effects use four grades, pooling AA and AAA. Other accounting controls are tangible assets/assets, revenue/assets, (operating profit plus depreciation)/assets, investment rate, log(1 + employees) and an IFRS indicator. Debt and cost controls are long-term liabilities/assets, interest-bearing debt/assets, long-term bank loans/assets, short-term bank loans/assets, the long-term share of bank loans and borrowing cost. The no-debt and no-bank-loan indicators are zero throughout this sample and are omitted. The Wald test is for the eight original characteristics, with standard errors clustered by firm.

bankruptcy in 2018. These windows follow account years because the data do not report exact filing or rating dates.

Grade boundaries. To set the boundaries in equation (2), I calculate the historical one-year bankruptcy rate for each of the four agency ratings from eligible accounts dated before t (Table A.6). The three cutoffs define four risk intervals, from AA+ at the lowest risk to C at the highest. If a predicted probability falls exactly on a cutoff, I assign the riskier grade.

A.3.2 Comparison of Bankruptcy Predictions

The sample contains 2,073,249 firm-years from 346,251 firms in 2008–2017, with 556 next-year bankruptcies. I calculate pooled AUCs using $-R_{it}^{A}$ and $-R_{it}^{F}$ as risk scores and give ties half credit. The fundamentals-based rating has a higher AUC in eight of the ten years. Agency ratings perform better in 2010 and 2015.

I screen the same share q of firms each year, ranking them by the agency rating or $\widehat{p}_{it}$. Tied firms at the cutoff enter proportionally. This rule also applies to ties created by isotonic calibration. Capture is the expected number of bankruptcies identified across all years divided by the total number of bankruptcies.

Table A.6: Grade Boundaries of the Fundamentals-Based Rating (Predicted Probability, Percent)

Year t	C / B	B / A	A / AA+
2008	0.234715	0.048148	0.014527
2009	0.192291	0.043956	0.012925
2010	0.159553	0.037449	0.011848
2011	0.170895	0.036602	0.012138
2012	0.155311	0.034804	0.011138
2013	0.146150	0.035120	0.011212
2014	0.131034	0.032419	0.010219
2015	0.130277	0.032393	0.010786
2016	0.134086	0.033813	0.011678
2017	0.132590	0.034671	0.012376

Notes: Each boundary is the geometric mean of the historical one-year bankruptcy rates of the two adjacent agency ratings, computed from accounts dated before t (equation (2)). A probability exactly at a boundary receives the riskier grade.

Table A.7. Risk Ranking and Next-Year Bankruptcy Capture

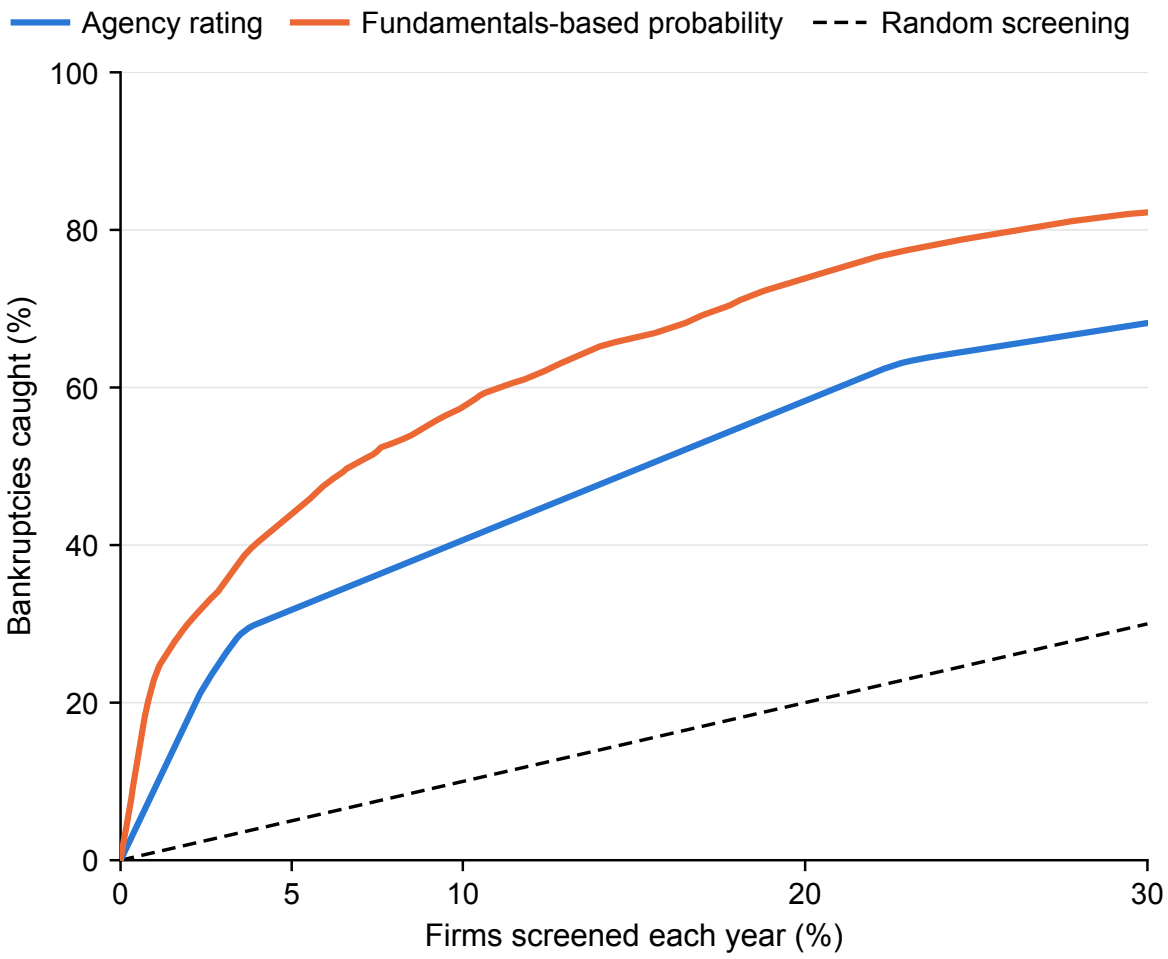
	Agency	Fundamentals	Difference	95% interval
Panel A. Four-grade rating AUC				
ROC AUC	0.7557	0.7822	0.0265	[0.0053, 0.0491]
Panel B. Agency rating versus continuous fundamentals probability				
Bankruptcies captured (%). Differences in percentage points				
Screen highest-risk 5%	31.79	43.93	12.14	[5.86, 18.42]
Screen highest-risk 10%	40.64	57.54	16.90	[11.06, 22.74]
Screen highest-risk 20%	58.34	73.87	15.53	[10.07, 20.98]
Screen highest-risk 30%	68.18	82.22	14.04	[9.08, 19.00]

Notes. The sample contains 2,073,249 firm-years in 2008–2017 and 556 next-year bankruptcies. Panel A compares four-grade ratings. Panel B compares agency ratings with the continuous fundamentals probability. Differences are fundamentals minus agency. Intervals use 4,999 paired bootstrap draws of firms. Panel B intervals cover all four capture differences jointly.

I resample firms with replacement 4,999 times. Each draw keeps their full histories and uses the same firms for both scores. I recalculate screening cutoffs and tie fractions in each draw. The AUC difference has a percentile 95 percent interval. The capture intervals cover all four differences jointly, using the maximum absolute standardized bootstrap error. The fitted model, calibration, grade boundaries and calendar years remain fixed.

Table A.7 reports the AUC and capture differences. All reported 95 percent intervals exclude zero.

Figure A.1. Next-Year Bankruptcy Capture by Screening Share



Notes. Next-year bankruptcy capture in the 2008–2017 sample. Firms are ranked each year by agency ratings or $\widehat{p}_{it}$. Ties at the cutoff enter proportionally. The dashed line denotes random screening. Table A.7 reports confidence intervals.

A.3.3 Joint Distribution of the Two Ratings

Table A.8 shows how the fundamentals-based ratings are distributed within each agency rating. Rows are agency ratings and columns are fundamentals-based ratings, both ordered C, B, A and AA+. Panel A reports firm-year counts. Panel B divides each count by the total number of firm-years in its agency-rating row, so each row sums to 100 percent before rounding. Diagonal cells indicate agreement; off-diagonal cells indicate disagreement. Panels C and D retain the bankruptcy counts and rates in $t + 1$; Panel D provides the numerical values plotted in Figure 2.1.

Table A.8: Joint Distribution of Agency and Fundamentals-Based Ratings

	Fundamentals-based rating R^F				
Agency rating R^A	C	B	A	AA+	All
Panel A. Firm-years					
C	46,562	12,795	5,247	2,280	66,884
B	223,504	112,006	49,937	22,009	407,456
A	198,844	260,414	218,334	132,174	809,766
AA+	101,292	202,201	241,511	244,139	789,143
Panel B. Share of the agency rating's firm-years (%)					
C	69.6	19.1	7.8	3.4	100.0
B	54.9	27.5	12.3	5.4	100.0
A	24.6	32.2	27.0	16.3	100.0
AA+	12.8	25.6	30.6	30.9	100.0
Panel C. Bankruptcies in $t + 1$					
C	140	14	4	1	159
B	161	26	6	0	193
A	106	28	9	5	148
AA+	32	13	6	5	56
Panel D. Bankruptcy rate in $t + 1$ (%)					
C	0.3007	0.1094	0.0762	0.0439	0.2377
B	0.0720	0.0232	0.0120	0.0000	0.0474
A	0.0533	0.0108	0.0041	0.0038	0.0183
AA+	0.0316	0.0064	0.0025	0.0020	0.0071

Notes: All 2,073,249 firm-years in the measurement sample, 2008–2017. AA+ pools AA and AAA. Rows are agency ratings; columns are fundamentals-based ratings. Panel B divides each cell's count by the total firm-years in its agency-rating row; percentages may not sum to 100 because of rounding. The two ratings agree (diagonal cells) in 29.95 percent of firm-years. Panel D divides Panel C by Panel A and multiplies by 100; its four grade columns underlie Figure 2.1.

A.3.4 Distribution of the Rating Wedge

Table A.9 summarizes the direction and size of disagreement. The wedge is $W_{it} = R^A_{it} - R^F_{it}$, with C, B, A and AA+ coded as 1, 2, 3 and 4. A positive wedge means that the

agency rating is more favorable than the fundamentals-based rating. Panel A reports the count and share of firm-years at each value from −3 to 3. Panel B reports agreement, positive and negative wedges, the size of the absolute grade difference, and the mean and standard deviation. All shares use the full measurement sample as the denominator, including the shares with a one-grade or larger difference. These statistics describe disagreement between the two ratings. The positive and negative shares depend on predicted-risk calibration and the grade boundaries.

Table A.9: Distribution of the Rating Wedge

Panel A. Full distribution		
Wedge W	Firm-years	Share (%)
−3	2,280	0.11
−2	27,256	1.31
−1	194,906	9.40
0	621,041	29.95
1	725,429	34.99
2	401,045	19.34
3	101,292	4.89
All	2,073,249	100.00
Panel B. Summary statistics		
Statistic		Value
Agreement ($W = 0$), percent		29.95
Agency more favorable ($W > 0$), percent		59.22
Agency less favorable ($W < 0$), percent		10.83
One-grade difference ($\|W\| = 1$), percent		44.39
Difference of at least two grades ($\|W\| \geq 2$), percent		25.65
Mean wedge, grades		0.760
Standard deviation, grades		1.069

Notes: All 2,073,249 firm-years in the measurement sample, 2008–2017, with equal weight for each firm-year. $W = R^A - R^F$, where agency and fundamentals-based ratings are coded C=1, B=2, A=3 and AA+=4. A positive wedge indicates a more favorable agency rating. All percentage shares use the full sample as the denominator, including the shares with $|W| = 1$ and $|W| \geq 2$. The standard deviation uses the sample denominator $N - 1$. Positive and negative shares depend on the calibration of predicted probabilities and the grade boundaries.

A.4 Further Evidence on Bankruptcy within Agency Ratings

Predicted-risk groups. I extend equation (5) to the full measurement sample by replacing H_{it} with indicators for Q2, Q3 and Q4, with Q1 as the reference group. Q1 and Q4 retain the bottom- and top-quartile groups used in the main text. The remaining observations are split at the median predicted probability for the same agency rating and year. Table A.10 reports this single logit regression with agency-rating and year

effects. Relative to Q1, the estimated odds ratios are 1.34 for Q2, 2.35 for Q3 and 6.69 for Q4. The three group coefficients are jointly significant (Wald $\chi^2(3) = 306.35$, $p < 0.001$).

Table A.10: Next-Year Bankruptcy across Predicted-Risk Quartile Groups

	Q1 (lowest)	Q2	Q3	Q4 (highest)
Coefficient	Reference	0.295	0.853***	1.901***
		(0.182)	(0.175)	(0.140)
Odds ratio	1.00	1.34	2.35	6.69
Firm-years in group	733,155	472,040	249,881	618,173
Bankruptcies in group	60	61	76	359
Agency-rating effects		Yes		
Year effects		Yes		

Notes: One logit regression of bankruptcy in $t + 1$ on indicators for Q2, Q3 and Q4, with Q1 as the reference group, and additive agency-rating and year effects. Groups use predicted next-year bankruptcy probability within each agency rating and year, 2008–2017. Q1 includes values at or below the 25th percentile; Q4 includes values at or above the 75th percentile. The remaining observations are split at the median of the full agency-rating-year cell, with values equal to the median assigned to Q2. Ties remain together. The sample contains 2,073,249 firm-years from 346,251 firms. Standard errors clustered by firm in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Horizons and wedge categories. Table A.11 re-estimates equation (4) with bankruptcy dated exactly h years after t. At each horizon the sample keeps the firm-years that have not failed before $t + h$ and whose event year lies inside the bankruptcy register, so the rating years end in $2018 - h$. The coefficient is positive and significant at every horizon. Table A.12 replaces the linear wedge with an indicator for each nonzero value; the coefficients rise monotonically from $W = -3$ to $W = +3$.

Table A.11: The Rating Wedge and Bankruptcy at Longer Horizons

	Bankruptcy exactly h years after t (logit)				
	$h = 1$	$h = 2$	$h = 3$	$h = 4$	$h = 5$
Rating wedge W_{it}	1.205***	0.358***	0.381***	0.367***	0.297***
	(0.092)	(0.015)	(0.011)	(0.012)	(0.014)
Odds ratio	3.34	1.43	1.46	1.44	1.35
Firm-years at risk	2,073,249	1,819,183	1,568,157	1,324,854	1,097,436
Bankruptcies at $t + h$	556	10,081	16,224	12,567	9,097
Rating years	2008–2017	2008–2016	2008–2015	2008–2014	2008–2013

Notes: Logit estimates of equation (4) with the outcome dated $t + h$. Agency-rating effects (four grades) and year effects in every column. The sample at horizon h keeps firm-years that have not failed before $t + h$ and whose event year lies inside the bankruptcy register ($t + h \leq 2018$). Column $h = 1$ is column (1) of Table 2.2. Standard errors clustered by firm in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Table A.12: Next-Year Bankruptcy by Wedge Category within Agency Ratings

	$W = -3$	$W = -2$	$W = -1$	$W = +1$	$W = +2$	$W = +3$
Coefficient	-2.439^{**}	-1.911^{***}	-0.993^{***}	1.120^{***}	2.570^{***}	3.923^{***}
	(1.002)	(0.515)	(0.219)	(0.166)	(0.227)	(0.358)
Odds ratio	0.09	0.15	0.37	3.07	13.06	50.56

Notes: One logit regression of bankruptcy in $t+1$ on indicators for the six nonzero values of W_{it} ($W = 0$ omitted), with agency-rating and year effects, on all 2,073,249 firm-years (556 bankruptcies). Standard errors clustered by firm in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

A.5 Facts 2 and 3: Sample, Variables and Further Results

Sample. All four outcomes in Table 2.3 use the financing sample constructed in Appendix A.1, with 996,989 firm-years from 172,489 firms.

Outcomes. The borrowing cost is external interest expense at $t+1$ over interest-bearing debt at $t+1$, winsorized at the annual 1st and 99th percentiles, in basis points. Debt D is the sum of long-term bank loans, short-term bank loans and bonds; its growth g is equation (7), zero when D is zero in both years. For small changes, g is approximately 100 times the log change in D. The extensive-margin outcomes are $100 \times \mathbf{1}\{D_{i,t+1} > 0\}$ and $100 \times \mathbf{1}\{L_{i,t+1} > 0\}$, where L is long-term bank loans.

Controls. X_{it} contains log assets, tangible assets over assets, return on assets, sales over assets, cash over assets, operating profit plus depreciation over assets, leverage, the short-term share of liabilities, an indicator for no debt, interest-bearing debt over assets, long- and short-term bank loans over assets, the long-term share of bank loans, an indicator for no bank loans, and a cubic in the standardized log of $\widehat{p}_{it}$. Ratios are bounded at annual 1st and 99th percentiles that are fixed on the firm-years with complete accounts before outcomes are selected.

Weights. For fundamentals-based rating f, the weight is

$$\omega_{it} = \begin{cases} 1, & W_{it} \neq 0, \\ N_{f,W\neq 0}/N_{f,W=0}, & W_{it} = 0, \end{cases} \tag{42}$$

where the counts come from the 2,073,249 firm-years of the measurement sample. Within each fundamentals-based rating, firm-years in which the two ratings agree and firm-years in which they disagree thus carry the same total weight. The weights are the same for all outcomes and all specifications.

Wedge categories and rating pairs. Table A.13 replaces the linear wedge with indicators for its nonzero values, and Table A.14 with an indicator for each pair of grades that disagree, compared with agreeing firm-years in the same fundamentals-based rating and year. Both use the common sample before the screen on debt balances (997,800 firm-years) and, as loan outcome, long-term bank loans at $t + 1$ over total assets at t. Firms rated above their fundamentals pay less, and firms rated below pay more, in every category and in all but one pair. The loan ratio is higher in every pair rated above its fundamentals and lower in every pair rated below; with the linear wedge, it is 181.6 percentage points of initial assets higher per grade.

Table A.13: Borrowing Cost and Long-Term Bank Loans by Wedge Category

	Borrowing cost (bp)	Long-term bank loans at $t+1$ over assets at t (pp)
Rating wedge W_{it} (linear)	-60.10^{***}	181.6^{***}
	(3.51)	(52.2)
$W = -3$	249.74^{***}	-312.7^{***}
	(35.84)	(121.2)
$W = -2$	56.19^{***}	-228.4^{*}
	(7.93)	(131.1)
$W = -1$	11.23^{***}	-211.3^{**}
	(3.79)	(104.3)
$W = +1$	-109.84^{***}	34.4
	(5.13)	(72.0)
$W = +2$	-129.70^{***}	388.0^{***}
	(7.51)	(114.4)
$W = +3$	-135.72^{***}	740.2^{*}
	(12.67)	(381.3)
Firm-years	997,800	997,800
Firms	172,544	172,544

Notes: The first row is a separate regression with the linear wedge; the other rows enter one regression with indicators for each nonzero wedge value ($W = 0$ omitted). Controls, fixed effects and weights as in Table 2.3. The sample is the common sample before the screen for nonnegative debt balances, which removes 811 firm-years from Table 2.3. The loan ratio is not capped. Standard errors clustered by firm in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Size groups and maturity. The size groups are the quintiles of log total assets among the 2,066,374 rated firm-years with complete accounts, computed separately for each year before outcomes are selected. In the regressions by size, the wedge, the controls and the fundamentals-based-rating-by-year effects are interacted with the size group; industry-by-year effects are common. Panel B of Table A.15 splits bank loans by maturity: the outcomes are the growth rates of long-term and of short-term bank loans, defined

Table A.14: Borrowing Cost and Long-Term Bank Loans by Rating Pair

Fundamentals-based rating	Agency rating	Borrowing cost (bp)	Long-term bank loans at $t+1$ over assets at t (pp)
Panel A. Agency rating more favorable ($W > 0$)			
C	B	-278.06^{***}	42.4
		(12.21)	(80.3)
C	A	-313.40^{***}	799.7^{***}
		(13.99)	(288.5)
C	AA+	-222.65^{***}	833.9^{**}
		(15.43)	(391.2)
B	A	-29.95^{***}	5.7
		(4.64)	(171.1)
B	AA+	-10.94^{*}	93.3
		(6.29)	(109.6)
A	AA+	-10.81^{**}	92.5
		(4.57)	(93.9)
Panel B. Agency rating less favorable ($W < 0$)			
B	C	229.45^{***}	-87.3
		(17.62)	(173.6)
A	C	178.02^{***}	-182.9^{*}
		(24.37)	(110.3)
A	B	12.57^{**}	-215.4^{**}
		(5.31)	(106.4)
AA+	C	237.64^{***}	-310.8^{***}
		(35.87)	(111.0)
AA+	B	30.52^{***}	-228.5^{*}
		(8.29)	(117.8)
AA+	A	-1.93	-210.0^{**}
		(5.01)	(83.5)
Firm-years		997,800	997,800
Firms		172,544	172,544

Notes: One regression per outcome with an indicator for each of the twelve rating pairs in which the two ratings differ. Each pair is compared with firm-years whose agency rating equals the fundamentals-based rating, within the same fundamentals-based rating and year. Controls, fixed effects, weights and sample as in Table A.13. Standard errors clustered by firm in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

as in equation (7). These regressions add bonds and intra-group loans over assets to the controls and use the 995,971 firm-years that report intra-group loans.

Table A.15: Responses to the Rating Wedge by Firm Size

	S1	S2	S3	S4	S5
Panel A. Outcomes of Table 2.3 (Figure 2.3)					
Borrowing cost (bp)	−107.74***	−109.90***	−68.23***	−26.01***	−7.25
	(11.95)	(8.90)	(7.21)	(5.85)	(5.39)
Debt growth (pp)	5.47***	2.35***	0.12	−0.51	−0.95***
	(0.55)	(0.38)	(0.33)	(0.32)	(0.31)
Has bank or bond debt (pp)	2.46***	1.15***	0.44***	0.40***	0.19
	(0.26)	(0.16)	(0.14)	(0.13)	(0.13)
Has long-term bank loan (pp)	2.21***	1.03***	0.33**	0.11	0.55***
	(0.23)	(0.16)	(0.15)	(0.14)	(0.14)
Panel B. Growth of bank loans by maturity					
Long-term bank loans (pp)	4.98***	2.85***	1.87***	0.61**	0.25
	(0.49)	(0.36)	(0.32)	(0.29)	(0.29)
Short-term bank loans (pp)	0.00	−1.50***	−3.26***	−2.29***	−2.40***
	(0.44)	(0.32)	(0.33)	(0.32)	(0.31)
Panel C. The size groups					
Median assets (NOK million)	0.22	1.05	2.78	7.04	33.22
No debt at t (%)	72.1	49.7	39.7	34.7	37.0
Fundamentals-based rating C (%)	57.2	43.9	30.4	15.7	9.0
Share of firm-years (%)	9.4	16.1	21.3	24.7	28.5
Share of debt at t (%)	0.1	0.3	1.4	4.5	93.7

Notes: Coefficients on W_{it} per grade. S1–S5 are quintiles of log total assets among all rated firm-years with complete accounts, computed year by year before outcomes are selected (S1 below NOK 0.35–0.67 million, S5 above NOK 11.9–12.9 million). Panel A: one regression per outcome in which W_{it}, the controls and the fundamentals-based rating × year effects are interacted with the size group; industry × year effects are common; the pooled estimates are in Table 2.3. Panel B: growth rates defined as g in Table 2.3, separately for long-term and short-term bank loans; same specification, with bonds and intra-group loans over assets added to the controls, on the 995,971 firm-years that report intra-group loans. Panel C: medians and shares in the sample of Table 2.3; debt is bank and bond debt. Standard errors clustered by firm in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

A.6 Upgrades and Later Bankruptcy

Design. Let t be a year in which the agency rating may change relative to $t-1$. The sample keeps the firm-years whose fundamentals-based rating is unchanged and whose agency rating stays the same or rises by one step,

$$\Delta R^F_{it} = 0, \qquad \Delta R^A_{it} \in \{0, 1\}, \qquad U_{it} = \mathbf{1}\{\Delta R^A_{it} = 1\},$$

so that within the sample the wedge rises only through the agency rating. Firms rated AA+ at $t-1$ cannot be upgraded on the four-grade scale and are excluded. Event years run from 2009 to 2013, which leaves five years of bankruptcy follow-up through 2018.

For $h = 1, \ldots, 5$, I estimate

$$Y_{it}^{(h)} = \theta_h U_{it} + X'_{i,t-1}\gamma_h + \alpha_i^{(h)} + \lambda^{(h)}_{R^A_{i,t-1}, R^F_{i,t-1}, t} + \varepsilon_{it}^{(h)}, \tag{43}$$

where $\lambda^{(h)}_{R^A_{i,t-1}, R^F_{i,t-1}, t}$ denotes fixed effects for each initial rating pair and event year. Each pair combines the agency rating and the fundamentals-based rating, both measured at $t-1$. Initial agency ratings are C, B or A, and initial fundamentals-based ratings are C, B, A or AA+. The effects vary across event years 2009–2013 and are estimated separately for each horizon h. The vector $X_{i,t-1}$ contains a spline in pre-event predicted risk, pre-event financial characteristics, and rating and financial changes from $t-2$ to $t-1$, and $\alpha_i^{(h)}$ are firm effects. The outcomes are bankruptcy by year $t+h$, $F_{it}^{(h)} = \mathbf{1}\{t < T_i \leq t+h\}$, and bankruptcy in year $t+h$, $J_{it}^{(h)} = \mathbf{1}\{T_i = t+h\}$, where T_i is the firm's bankruptcy year. Each annual bankruptcy probability uses the full event-year sample. The coefficient for $F^{(h)}$ equals the sum of the coefficients for $J^{(1)}, \ldots, J^{(h)}$. The firm effects are identified from firms with more than one eligible event year; after singletons are removed, the sample has 60,633 firm-years of 27,023 firms. A firm can contribute several event years, so windows overlap; standard errors are clustered by firm. The upgrade sample uses a sixteen-input version of the prediction model and a revised industry screen, and eligibility requires neither later accounts nor survival after the event year.

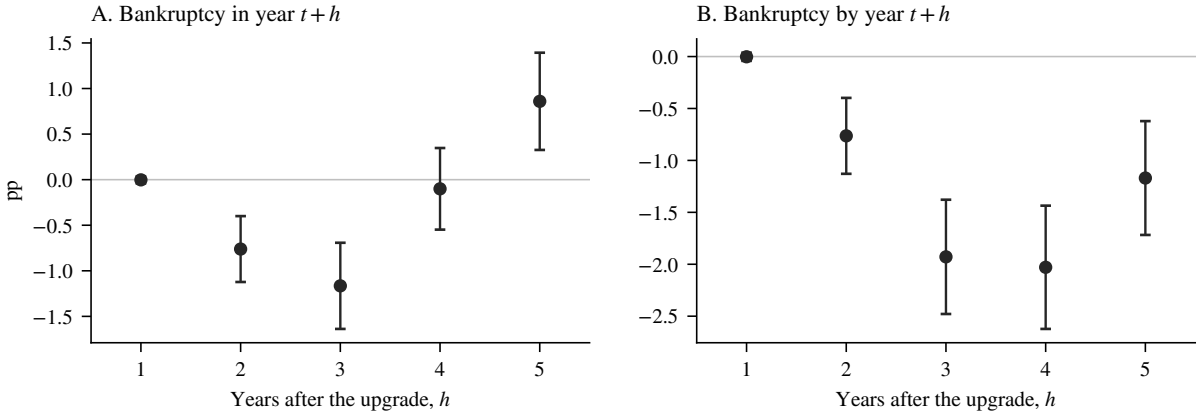
Results. Table A.16 and Figure A.2 report the coefficients. Column (2) of the table weights the firm-years by entropy-balancing weights that equate pre-event characteristics between upgrades and other firm-years. Table A.17 uses the same design with outcomes from the accounts: the change from $t-1$ to $t+h$ in external interest expense over assets at $t-1$, and in an indicator that operating profit is below external interest expense. These samples require accounts at $t-1$ and $t+h$.

Table A.16: Agency Upgrades at an Unchanged Fundamentals-Based Rating and Later Bankruptcy

	(1)	(2)
Bankruptcy in year 5	0.859***	0.960***
	(0.272)	(0.322)
Bankruptcy by year 3	−1.929***	−1.889***
	(0.281)	(0.334)
Bankruptcy by year 5	−1.170***	−0.930***
	(0.280)	(0.341)
Difference: by year 5 − by year 3	0.759**	0.959**
	(0.338)	(0.399)
Firm effects	Yes	Yes
Entropy-balancing weights	No	Yes
Firm-years	60,633	60,633
Firms	27,023	27,023

Notes: Coefficients on the upgrade indicator U_{it} in equation (43), in percentage points. Each row is a separate regression on the same firm-years. "In year 5": bankruptcy exactly in $t + 5$; "by year h": bankruptcy in $t + 1, \ldots, t + h$. Every regression includes initial agency rating × initial fundamentals-based rating × event-year effects, pre-event risk and financial controls, and firm effects. The difference row uses the joint covariance of the two cumulative coefficients. Standard errors clustered by firm in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

Figure A.2: Bankruptcy after an Agency Upgrade, within Firms



Notes: Coefficients θ_h of equation (43), in percentage points, with 95 percent intervals. Panel A: bankruptcy exactly in year $t + h$; Panel B: bankruptcy by year $t + h$, the running sum of Panel A. Firm effects, equal weights, 60,633 firm-years (Table A.16, column (1)). Standard errors clustered by firm.

Table A.17: Interest Burden and Profit Shortfall after Agency Upgrades

	$h = 1$	$h = 3$	$h = 5$
Interest expense over assets: change from $t-1$ to $t+h$ (pp)			
Upgrade	−0.029	0.438***	0.377***
	(0.110)	(0.120)	(0.119)
Firm-years	55,644	49,719	44,395
Operating profit below interest expense: change in probability (pp)			
Upgrade	3.916***	7.966***	5.115***
	(1.495)	(1.526)	(1.552)
Firm-years	55,644	49,719	44,395

Notes: Same design as Table A.16, column (1): firm effects, initial-cell effects, pre-event controls, equal weights. Interest expense is external interest, scaled by assets at $t-1$. The profit-shortfall outcome is the change in an indicator for operating profit below external interest expense. Samples require accounts at $t-1$ and $t+h$. Standard errors clustered by firm in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

B Quantitative Implementation: Parameters and Validation Details

Table B.1 reports the firm and credit-assessment parameters. Table B.2 lists the labor, investment-finance, and intermediary parameters. The tables separate maintained assumptions, panel evidence and auxiliary estimates, parameters calibrated within the model, and derived quantities. The intermediary's divertible share and transfer to new bankers follow from the stationary conditions in Appendix E.4; aggregate shock parameters are listed separately. Parameter values are reported to two decimal places.

External parameter choices. The capital exponent is profit curvature after labor is optimized out, consistent with the interpretation in David and Venkateswaran (2019). The annual depreciation rate is the same as in Bordalo et al. (2026). Khan and Thomas (2013) provide reference values for the labor elasticity and annual discounting; their household discount factor also determines firms' discounting in steady state. The separate productivity estimates described in Section 4.1 are close to the private-firm estimates in Nikolov et al. (2021).

The banker survival probability implies a five-year expected horizon, as in Akinci and Queralto (2022). The reference spread and bank leverage are motivated by Gertler and Karadi (2011) and Gertler et al. (2020), respectively; they are reference targets, not estimates for Norwegian banks. Linear labor disutility follows Hansen (1985).

Investment finance. The required financing share $\omega_I = 0.40$ is motivated by financing coverage in the firm accounts. Using long-term bank credit and the model's amortization rate, aggregate borrowing including refinancing covers 0.38 to 0.53 of positive investment across samples. The comparison depends on the assumed amortization rate, because the accounts record debt stocks rather than new loans. Table B.3 compares stationary economies under fundamentals-based pricing, with the fixed operating cost recalibrated in each to preserve the incumbent default target. With $\omega_I = 0.40$, the coverage ratio is 0.58, above the range in the accounts. Coverage is an outcome, not the parameter itself: firms may borrow more than the restriction requires. The model also has a much larger share of investing firms than the accounts. Both differences limit how precisely aggregate coverage can discipline a requirement imposed on every investing firm.

Investment and the cost of credit. The investment-financing restriction makes investment sensitive to the price of debt. The comparison uses the recalibrated stationary economies in Table B.3. Table B.4 raises the required lending return by 100 basis points, decaying at rate 0.8, with wages fixed. Investment falls on impact by 1.96 percent with $\omega_I = 0.40$ and by 0.54 percent without the restriction, and cumulated output over years

Table B.1: Firm and Credit-Assessment Parameters

Parameter	Description	Value	Source or Target
Assumptions			
α	Reduced-form capital exponent	0.62	David and Venkateswaran (2019)
δ	Capital depreciation rate	0.10	Bordalo et al. (2026)
β_f	Firm discount factor	0.96	Khan and Thomas (2013)
ξ	Capital recovery fraction	0.20	Predetermined
Panel evidence and auxiliary estimates			
ρ_z	Productivity persistence	0.74	Panel AR(1) estimate
σ_z	Productivity innovation s.d.	0.32	Two-year autocovariances
ρ_W	Assessment-state persistence	0.87	Auxiliary AR(1) fit
π_x	Exogenous exit probability	0.05	Firm exits
Parameters calibrated within the model			
F	Fixed operating cost	0.65	Bankruptcy rate
ϕ_b^+	Debt adjustment cost, increase	0.95	Median leverage
ϕ_b^-	Debt adjustment cost, decrease	3.25	Leverage s.d.
ϕ_k	Capital adjustment cost	1.23	Mean investment rate
σ_W	Assessment innovation s.d.	0.69	Rating-gap dispersion
γ	Maturing fraction of debt	0.12	Leverage autocorrelation
η_W	Perceived long-run mean loading	0.07	Within-grade default
Derived reference quantities			
R_f	Reference gross lending return	1.04	Rounded $1/\beta_f$
c	Coupon rate	0.04	$R_f - 1$

Notes: One period is one year; innovation standard deviations are annual. Values are rounded to two decimal places. The last column lists supporting references or the main informative moment, not a separate one-moment estimate for each parameter. Section 4.1 describes the persistence estimates. α is the capital exponent after labor is optimized out, as in (11).

Table B.2: Labor, Investment Finance, and Intermediary Parameters

Parameter	Description	Value	Source or Target
Assumptions and normalizations			
ν	Labor elasticity	0.60	Khan and Thomas (2013)
σ_C	Consumption curvature	2.00	Arellano et al. (2019)
ζ	Inverse Frisch elasticity	0.50	Arellano et al. (2019)
χ	Labor disutility weight	Pending	Baseline average hours equal one
σ_m	Cash-flow shock scale	0.03	Predetermined
μ_z	Mean log productivity	0.00	Normalization
μ_W	Stationary mean wedge	0.19	Baseline setting
θ_B	Banker survival	0.80	Five-year horizon; Akinci and Queralto (2022)
Financing evidence and stationary reference targets			
ω_I	Required investment-financing share	0.40	Coverage evidence
$\bar{s}_C$	Reference lending spread	0.01	Gertler and Karadi (2011)
$\bar{\phi}_C$	Reference bank leverage	10.00	Gertler et al. (2020)
Parameters derived from stationary conditions			
R^*	Gross foreign funding rate	1.03	$R_f - \bar{s}_C$
β_B	Banker discount factor	0.97	$1/R^*$
λ_B	Divertible asset fraction	0.18	Stationary conditions
ω_B	Entrant-bank transfer / assets	0.01	Stationary conditions
Aggregate shock specification			
A_0, ρ_A	Productivity index: impact and persistence	0.95, 0.80	Recession experiment

Notes: One period is one year. Values are rounded to two decimal places. The subscript C denotes the fundamentals-based economy. Intermediary parameters follow (68). The labor disutility weight χ is calibrated in the baseline economy and held fixed in the fundamentals-based pricing counterfactual. It satisfies $\chi = \frac{\bar{w}_W}{\bar{C}_W^{\sigma_C} \bar{L}_W^{\zeta}}$, where bars denote stationary values and the subscript W denotes the baseline economy. Household consumption excludes net payouts to foreign bank owners. Financing coverage in Table B.3 is a model outcome distinct from ω_I.

Table B.3: Investment Finance under Fundamentals-Based Pricing

Parameter or Moment	$\omega_I = 0$	$\omega_I = 0.40$
Fixed operating cost F	0.72577	0.63962
Incumbent default rate (%)	1.222	1.221
Aggregate debt / capital	0.346	0.681
Bank cash / positive investment	0.300	0.583
Share of operating mass investing (%)	89.99	91.70
Payouts / operating return before fixed costs	0.444	0.432

Notes: Both columns use fundamentals-based pricing, with fixed wages and lending returns. Each has its own stationary equilibrium; the fixed cost preserves the incumbent default target. Bank cash sums signed net issuance $q[b' - (1-\gamma)b]$ across operating firms; positive investment sums $[i]_+$. This aggregate ratio differs from the firm-level financing restriction in (16).

0–10 falls by 3.7 and 1.5 percent-years. In this recalibrated comparison, the impact response of investment is 3.6 times and the cumulated output response 2.5 times as large.

Table B.4: Responses to a Higher Lending Return

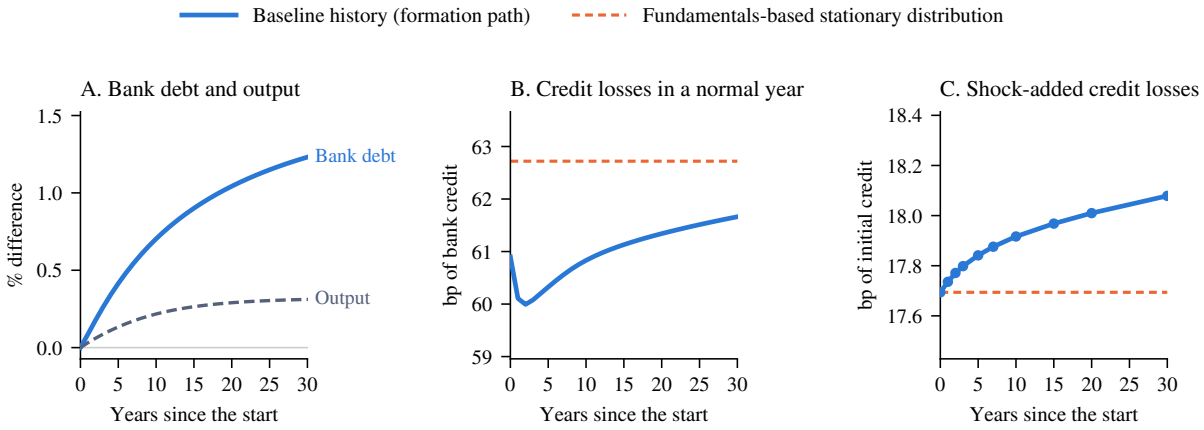
Response	$\omega_I = 0$	$\omega_I = 0.40$
Investment, impact (%)	−0.543	−1.957
Investment, cumulative (percent-years)	−3.826	−10.315
Output, year 1 (%)	−0.053	−0.177
Output, cumulative (percent-years)	−1.451	−3.689

Notes: Starting from the economies in Table B.3, the lending return rises by $0.01(0.8)^t$ while wages stay fixed. Responses are relative to each economy's no-shock path, as a percentage of its stationary level. Cumulative responses sum years 0–10.

C The Allocation of Future Risk: Additional Results

A less persistent wedge. Figure C.1 and Table C.1 repeat Figure C.3 and Table 5.2 with $\rho_W = 0.5$. Credit grows more than at the baseline persistence, by 1.2 percent over 30 years and by 1.5 percent in the long run, and output rises by about 0.3 percent. The risk per unit of credit grows more slowly: shock-added losses per unit of initial credit are 2.2 percent above the counterfactual's after 30 years. In the long run the baseline history adds 0.81 basis points of initial credit to shock-added losses, 4.6 percent of the fundamentals-based history's. The allocation of credit across risk groups accounts for 66 percent of the difference and credit volume for 29 percent; loss rates within risk groups contribute 3 percent, against 16 percent at the baseline persistence, and entrants 2 percent.

Figure C.1: The Evolution of Credit and Risk Exposure, $\rho_W = 0.5$



Notes: As in Figure C.3, with $\rho_W = 0.5$. The high-risk share of credit along the path is not available for this persistence.

Levels and alternative splits. Table C.2 reports, at both persistences, the levels behind Tables 5.2 and C.1, the split of their Panel A averaged over the six orderings of its first three factors, and each risk group's contribution. Averaging over the orderings moves no share by more than 0.6 percentage points. Counted group by group, high-risk firms account for 94 percent of the additional losses at the benchmark persistence and for 92 percent at $\rho_W = 0.5$.

Who responds and who holds the additional debt. Figure C.2 separates the firms whose borrowing responds to a better assessment from the firms that hold the baseline's additional debt in the long run. In the same-state experiment of Figure 4.1, the smallest capital quintile accounts for 79 percent of the borrowing response and holds 4 percent of bank loans (Panel A). In the stationary distributions, high-risk states hold 111 percent of the additional debt, spread across all size quintiles, while low-risk states, mostly

Table C.1: Credit Allocation and Shock-Added Losses, $\rho_W = 0.5$

A. Sources of the difference in shock-added losses

	bp	Share (%)
Credit volume	+0.238	29
Allocation across risk groups	+0.537	66
Loss rates within risk groups	+0.026	3
Entrants	+0.013	2
Total: 18.51 against 17.69	+0.815	100

B. Credit shares and loss rates by risk group

	Share of credit (%)		Loss rate (bp)	
	Fundamentals-based history	Baseline history	Fundamentals-based history	Baseline history
High-risk firms	19.81	20.66	65.83	65.75
Low-risk firms	78.04	77.11	3.81	3.87
Largest 1% of firms	2.16	2.23	1.41	1.45

Notes: $\rho_W = 0.5$; otherwise as in Table 5.2.

among the largest firms, hold less debt than in the counterfactual (Panel B). Splitting the difference in chosen debt into a different distribution of firms across states and different borrowing at the same state attributes 92 percent to the distribution (91 percent with the order of the two terms reversed). Within each size and risk group, the two books lose almost the same amount per unit of credit under the common recession scenario (Panel C), so the additional losses reflect where credit sits. High-risk firms in the two smallest quintiles account for 50 percent of the additional losses, those in the middle quintile for 25 percent, and those in the two largest quintiles for 20 percent.

Credit and risk along the formation path. Figure C.3 shows the complete paths behind Table 5.1.

Further responses to a one-notch assessment improvement. In Figure 5.1, the mean assessment advantage halves within four years. The average loan spread falls by 78 basis points on impact and closes half the gap within about three years. Weighted by loans, it falls by 62 basis points and closes half the gap within about five years. The default rate falls by 0.25 percentage points on impact.

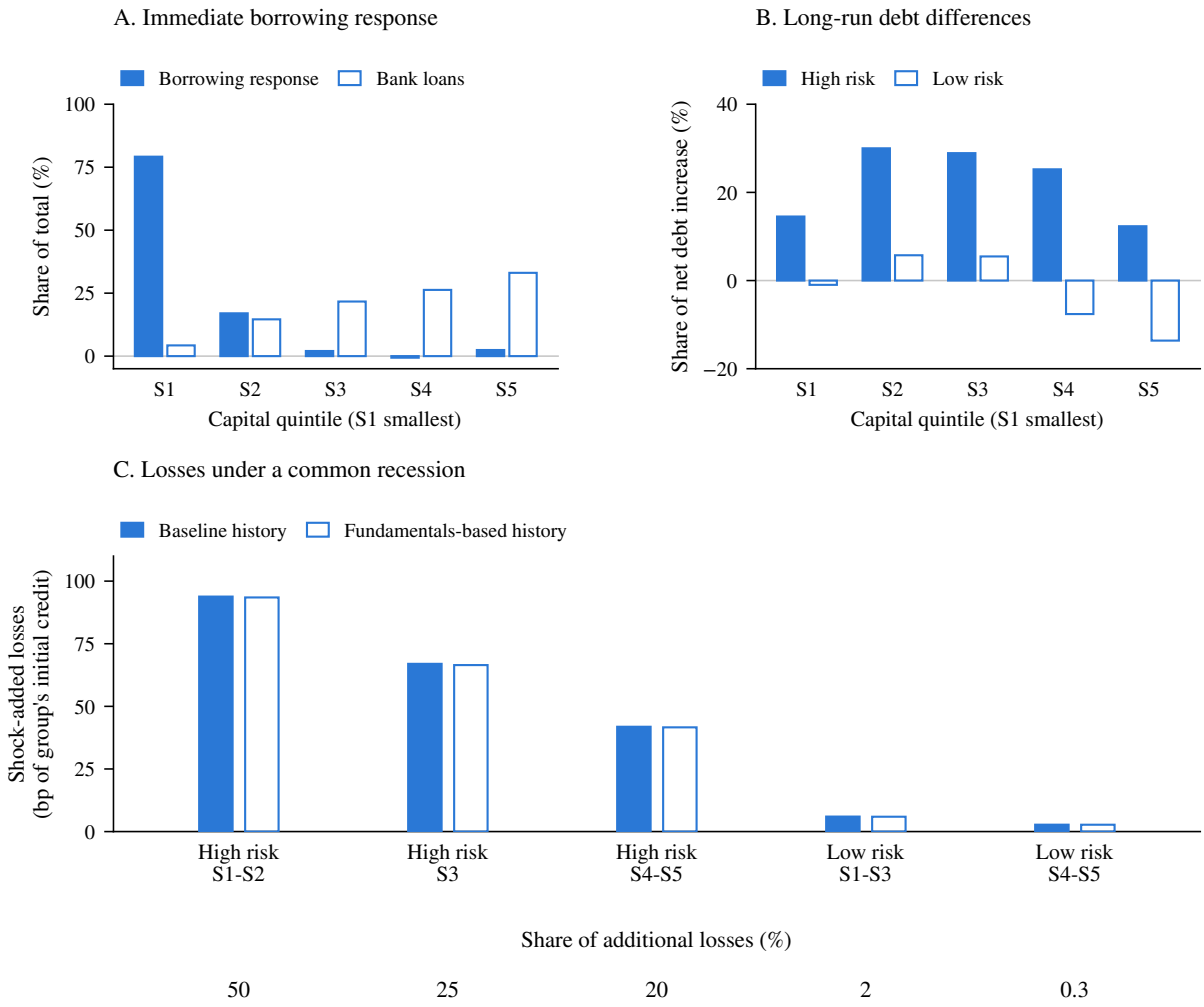
Bank debt peaks in year eight, 0.73 percent above the path without the assessment shift. The high-risk credit share peaks in year six, 0.31 percentage points higher. These gaps halve 17 and 25 years after their respective peaks. Additional shock-added losses peak in year five and halve 19 years later. By year 14, the assessment advantage is a tenth of its initial rise, while additional shock-added losses remain three-quarters of their peak.

Table C.2: Shock-Added Losses: Levels and Alternative Splits

	Benchmark		$\rho_W = 0.5$	
A. Levels				
	Fund.-based	Baseline	Fund.-based	Baseline
Bank credit (index)	100.00	100.88	100.00	101.49
Shock-added losses (bp)[a]	17.69	18.48	17.69	18.51
per unit of own credit (bp)	17.69	18.32	17.69	18.24
Normal-year losses (bp a year)[b]	62.72	62.75	62.72	62.54
B. Sources of the difference, averaged over orderings				
	bp	Share (%)	bp	Share (%)
Credit volume	+0.144	18	+0.243	30
Allocation across risk groups	+0.495	63	+0.532	65
Loss rates within risk groups	+0.126	16	+0.026	3
Entrants	+0.024	3	+0.013	2
Total	+0.790	100	+0.815	100
C. Contributions by risk group				
	bp	Share (%)	bp	Share (%)
High-risk firms	+0.743	94.2	+0.748	91.9
Low-risk firms	+0.021	2.6	+0.050	6.2
Largest 1% of firms	+0.001	0.2	+0.002	0.3
Entrants	+0.024	3.1	+0.013	1.6
Total	+0.790	100	+0.815	100

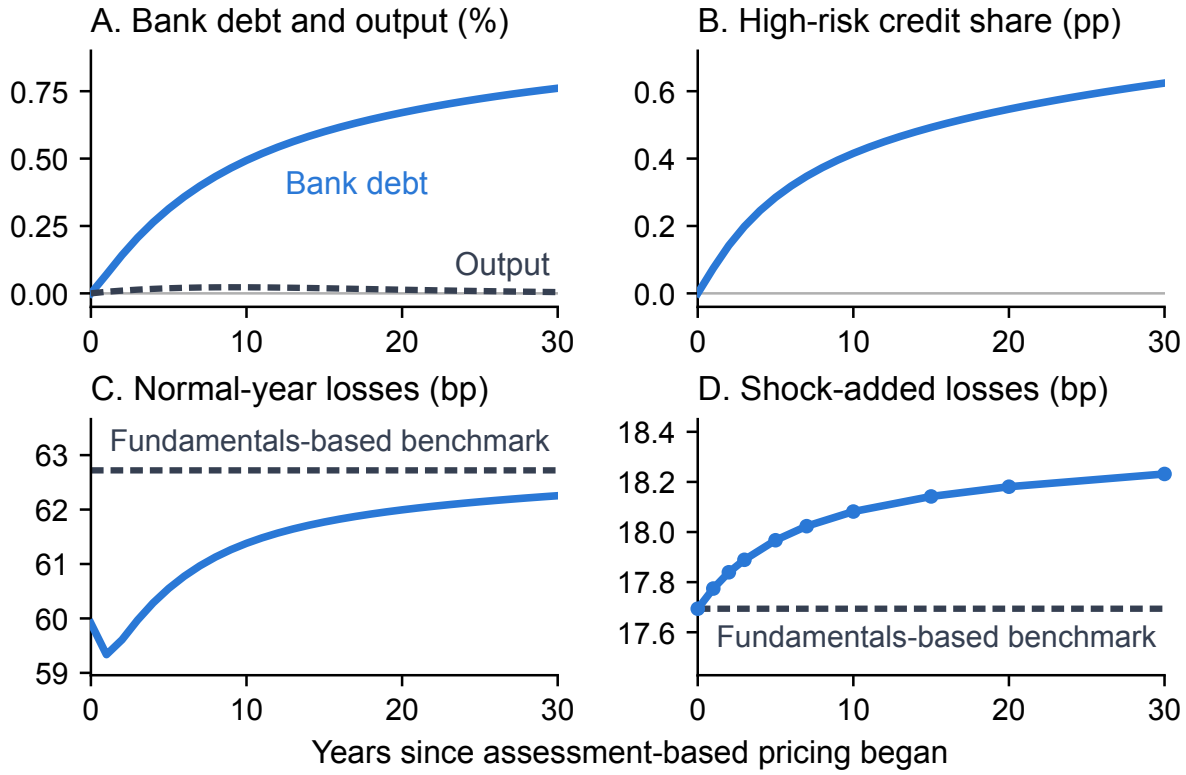
Notes: The recession and pricing rules follow Table 5.2. [a] Losses use the fundamentals-based history's initial credit as denominator, except the row marked "own credit." [b] Normal-year losses use each economy's own pricing and credit; the benchmark baseline value is year 100 in Figure C.3. Panel B averages the volume, allocation, and loss-rate contributions over all six replacement orders in (40). Panel C groups the extra losses by risk class. Entrants contribute their loss difference in both panels. Each panel sums to the total, in basis points of the fundamentals-based history's initial credit.

Figure C.2: Who Responds, Who Holds the Additional Debt, and Where the Losses Arise



Notes: $\mu_W = 0.19$; S1–S5 are capital quintiles, with S1 the smallest. Wages and the lending spread stay at their stationary values except under the common recession scenario of Panel C. Panel A: shares of the borrowing response to a one-notch better assessment at a given state (the experiment of Figure 4.1) and of bank loans. Panel B: contributions to the baseline's net increase in stationary debt over the counterfactual, by size quintile and risk class of the state (high risk: the fundamentals-based contract carries a spread of at least 250 basis points); the shares add up to 100. Panel C reports shock-added losses for the two stationary books under the common recession scenario of Section 5.2, in basis points of each group's initial credit. The row below Panel C gives each group's share of the additional losses (entrants: 3 percent).

Figure C.3: The Evolution of Credit and Risk Exposure



Notes: Both economies start in year 0 from the stationary distribution of the fundamentals-based pricing counterfactual. From year 0, lenders in one of them price debt with credit assessments drawn for each firm from the baseline's stationary distribution of assessments (the assessment-based path). Along these paths, aggregate productivity and the common wage remain at their steady-state levels. Each economy's lending spread is fixed at its own stationary value. Panel A: bank debt (blue) and output (gray), percent difference from year 0. Panel B: high-risk firms' share of bank loans, percentage-point difference from year 0; a firm is high risk if the fundamentals-based contract at its state carries a spread of at least 250 basis points. Panel C: credit losses in a year without a shock under the baseline's pricing, in basis points of current bank credit; dark gray dashed line: the counterfactual's stationary value. Panel D: at each marked date the distribution is copied and evaluated under the common recession scenario with fundamentals-based pricing (TFP falls by 5 percent; wages and the spread follow the counterfactual's general-equilibrium recession); shock-added losses (39) per unit of the copy's initial credit, in basis points; dark gray dashed line: the counterfactual's stationary book. $\mu_W = 0.19$. Long-run values are in Table 5.2 and Appendix Table C.2.

Capital rises by up to 0.41 percent in year 9, and output by 0.26 percent in year 8. Normal-year credit losses fall by 7 basis points per unit of credit on impact, from 63 without the shift, and remain below that path until year 17. Shock-added losses under the common recession scenario are higher from the first year.

D Aggregate Consequences: Additional Results

Responses to benchmark shocks. Table D.1 reports the impact and cumulative responses behind Figure 6.1. The bank-capital shock writes down 1 percent of intermediary assets through X_t. At stationary leverage of about ten, the write-down removes about 8 percent of net worth after banker turnover; the fall in the market value of long-term claims contributes to a total impact decline of about 23 log percentage points. The TFP shock lowers the productivity index by 5 percent and recovers at rate 0.8. The shocks differ in duration: over years 0–10, the counterfactual's investment falls by 1.42 percent-years after the bank-capital shock and by 6.75 after the TFP shock. The table separates years 0–2 from years 3–10 because investment subsequently recovers above its no-shock path in some economies.

A common initial contraction. Drechsel (2023) uses responses to different shocks to distinguish borrowing constraints. Here, Table D.2 compares the shocks at a common impact decline in the counterfactual's investment. For each shock s, I choose its size ε_s so that

$$-100 \log \frac{I_0^F(\varepsilon_s)}{I_0^F(0)} = a, \tag{44}$$

where $I_0^F(\varepsilon_s)$ is investment in the fundamentals-based economy in the year of a shock of size ε_s, and $I_0^F(0)$ is investment on its no-shock path. I then apply the same shock to the baseline. The two scales are $a = 1.16$, the impact decline after the benchmark write-down, and $a = 1.56$, the decline after the benchmark TFP shock. The recovery process is unchanged. The relative investment difference after the bank-capital shock is smaller at the larger scale.

Wages, hours, capital, and lending spreads. Figure D.1 shows the wage, hours, capital, and the common lending spread after the TFP and bank-capital shocks. Each economy is compared with its own no-shock path.

The labor-supply condition gives

$$\log \frac{w_t}{\bar{w}} = \sigma_C \log \frac{C_t}{\bar{C}} + \zeta \log \frac{L_t}{\bar{L}},$$

where bars denote each economy's stationary values. Higher consumption raises the wage the household requires to work the same hours. With consumption fixed, the household supplies fewer hours at a lower wage. Operating firms demand less labor at higher wages, holding capital and productivity fixed. Wages and hours adjust to clear the labor market.

Table D.1: Aggregate Responses to Benchmark Shocks

	Fundamentals-based	Baseline	Relative diff. (%)
TFP shock			
Investment, impact	−1.56	−1.60	+2.3
Investment, years 0–2	−3.65	−3.74	+2.5
Investment, years 3–10	−3.10	−3.11	+0.2
Investment, years 0–10	−6.75	−6.85	+1.5
Output, years 0–2	−4.76	−4.77	+0.2
Output, years 0–10	−9.51	−9.52	+0.1
Default rate, impact (pp)	0.1131	0.1177	+4.1
Default rate, years 0–2 (pp)	0.2582	0.2693	+4.3
Credit losses, years 0–10 (bp)	17.30	17.16	−0.8
Lending spread, impact (bp)	13.4	12.6	–
Net worth, largest fall	−2.0	−1.9	–
Bank-capital shock			
Investment, impact	−1.16	−1.22	+4.9
Investment, years 0–2	−1.52	−1.65	+8.4
Investment, years 3–10	0.10	−0.06	–
Investment, years 0–10	−1.42	−1.71	–
Output, years 0–2	−0.12	−0.14	+15.1
Output, years 0–10	−0.27	−0.33	+23.4
Default rate, impact (pp)	0.0068	0.0087	+27.6
Default rate, years 0–2 (pp)	0.0138	0.0183	+33.2
Credit losses, years 0–10 (bp)	0.88	0.80	–
Lending spread, impact (bp)	137.6	137.8	–
Net worth, largest fall	−22.8	−22.7	–

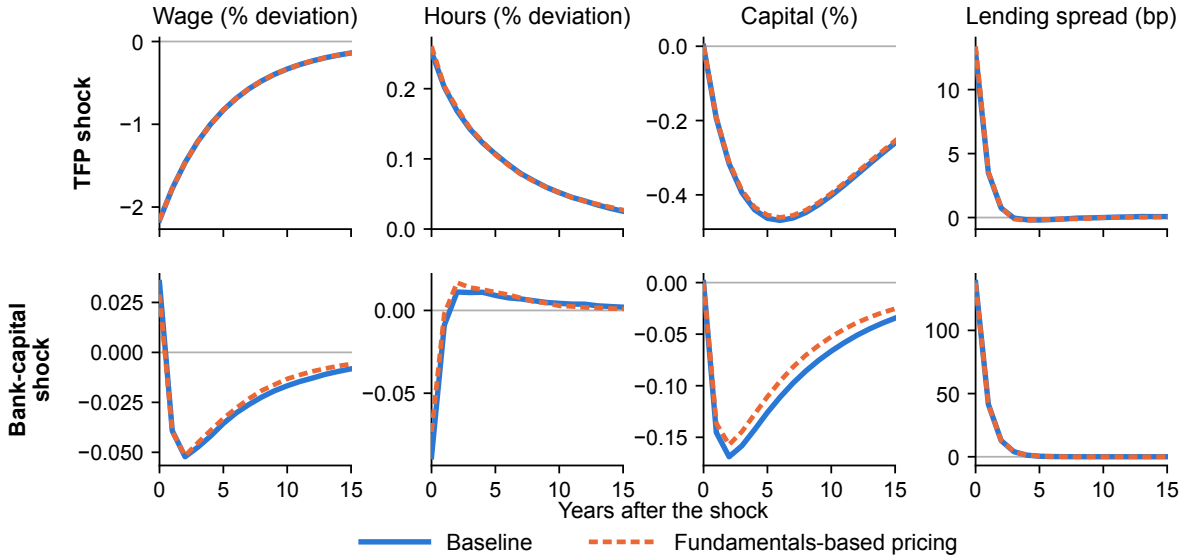
Notes: General-equilibrium responses to a 5% TFP decline with persistence 0.8 or a write-down of 1% of pre-shock bank assets. Each economy is compared with its own no-shock path. Investment and output are 100 times log changes; multi-year entries sum these changes (percent-years). Default rates are annual changes in percentage points, summed where indicated. Credit losses sum years 0–10, in basis points of fundamentals-based pre-shock credit. Net worth is the largest log decline over years 0–20, times 100. Relative difference is baseline minus fundamentals-based response, divided by the latter, in percent. – marks sign reversals, opposite signs across economies, or unreported spread and net-worth ratios.

Table D.2: Aggregate Responses at a Common Initial Contraction

	Fundamentals-based	Baseline	Relative diff. (%)
Initial investment decline: 1.16%			
Bank-capital shock: write-down of 1.00% of assets			
Investment, years 0–2	−1.52	−1.65	+8.4
Output, years 0–10	−0.27	−0.33	+23.4
Default rate, impact (pp)	0.0068	0.0087	+27.6
Credit losses, years 0–10 (bp)	0.88	0.80	–
TFP shock: TFP falls by 3.73%			
Investment, years 0–2	−2.69	−2.78	+3.3
Output, years 0–10	−7.05	−7.06	+0.1
Default rate, impact (pp)	0.0834	0.0798	−4.3
Credit losses, years 0–10 (bp)	12.90	12.68	−1.7
Initial investment decline: 1.56%			
Bank-capital shock: write-down of 1.26% of assets			
Investment, years 0–2	−2.00	−2.11	+5.7
Output, years 0–10	−0.36	−0.43	+18.1
Default rate, impact (pp)	0.0092	0.0111	+20.6
Credit losses, years 0–10 (bp)	1.01	0.96	–
TFP shock: TFP falls by 5.00%			
Investment, years 0–2	−3.65	−3.74	+2.5
Output, years 0–10	−9.51	−9.52	+0.1
Default rate, impact (pp)	0.1131	0.1084	−4.1
Credit losses, years 0–10 (bp)	17.30	17.16	−0.8

Notes: Each shock produces the stated initial investment decline in the fundamentals-based economy and is then applied at the same size to the baseline; see (44). Responses are relative to each economy's own no-shock path. Units and relative differences follow Table D.1. Multi-year responses sum years 0–10; default rates are changes on impact.

Figure D.1: Additional Aggregate Responses



Notes: The top row shows a 5 percent TFP decline with persistence 0.8; the bottom row shows a write-down of 1 percent of intermediary assets. Blue solid lines denote the baseline; orange dashed lines denote fundamentals-based pricing. The wage, hours, and capital are 100 times log deviations from each economy's own no-shock path. The lending spread is its deviation from the no-shock path in basis points. Vertical scales differ across panels.

A recalibrated alternative counterfactual. Table D.3 compares the baseline with a counterfactual that also prices debt with the true productivity process but whose fixed operating cost is chosen so that its stationary default rate equals the baseline's. Against this alternative, the baseline's investment falls 10 percent more over years 0–2 of the bank-capital shock and output 12 percent more over years 0–10, close to the differences in Table D.1. Its default rate rises 40 percent more on impact. The alternative changes the fixed operating cost and applies the household normalization in Table B.2. Its credit-loss comparison therefore combines changes in pricing with these calibration changes.

Supplementary common-price decompositions. Table D.4 reports four-way decompositions for three shocks at both values of ρ_W. The responses follow the firms present at date 0 and exclude subsequent entrants. Each history and pricing rule is compared with its own no-shock path. With the common aggregate price paths suppressed from

Table D.3: Aggregate Responses against a Recalibrated Alternative Counterfactual

	Recalibrated alternative	Baseline	Difference	Relative diff. (%)
TFP shock				
Investment, impact	−1.55	−1.60	−0.05	+3.3
Investment, years 0–2	−3.65	−3.74	−0.10	+2.6
Investment, years 3–10	−3.06	−3.11	−0.05	+1.6
Investment, years 0–10	−6.70	−6.85	−0.15	+2.2
Output, years 0–2	−4.76	−4.77	−0.01	+0.2
Output, years 0–10	−9.50	−9.52	−0.02	+0.2
Default rate, impact (pp)	0.1071	0.1084	+0.0012	+1.1
Default rate, years 0–2 (pp)	0.2424	0.2471	+0.0046	+1.9
Credit losses, years 0–10 (bp)	16.47	17.16	+0.68	+4.1
Lending spread, impact (bp)	12.8	12.6	−0.2	–
Net worth, largest fall	−1.9	−1.9	0.0	–
Bank-capital shock				
Investment, impact	−1.15	−1.22	−0.07	+6.2
Investment, years 0–2	−1.50	−1.65	−0.15	+10.0
Investment, years 3–10	−0.03	−0.06	−0.03	–
Investment, years 0–10	−1.53	−1.71	−0.18	–
Output, years 0–2	−0.12	−0.14	−0.02	+16.1
Output, years 0–10	−0.29	−0.33	−0.05	+16.4
Default rate, impact (pp)	0.0064	0.0087	+0.0023	+35.1
Default rate, years 0–2 (pp)	0.0123	0.0183	+0.0061	+49.3
Credit losses, years 0–10 (bp)	0.50	0.80	+0.29	–
Lending spread, impact (bp)	137.7	137.8	0.0	–
Net worth, largest fall	−22.9	−22.7	+0.1	–

Notes: The alternative uses fundamentals-based pricing and adjusts the fixed operating cost to match the baseline's stationary default rate. Other firm and bank parameters follow the fundamentals-based economy; household scaling follows Table B.2. Difference is baseline minus alternative; relative difference divides by the alternative response. Units follow Table D.1, including its credit-loss denominator.

the notation, the decomposition is

$$\begin{aligned}\mathcal{R}_{bb} - \mathcal{R}_{ff} = \quad & \underbrace{\mathcal{R}_{bf} - \mathcal{R}_{ff}}_{\text{Inherited distribution}} \\ & + \underbrace{\mathcal{R}_{fb} - \mathcal{R}_{ff}}_{\text{Current pricing}} \\ & + \underbrace{\mathcal{R}_{bb} - \mathcal{R}_{bf} - \mathcal{R}_{fb} + \mathcal{R}_{ff}}_{\text{Interaction}}.\end{aligned} \tag{45}$$

Here the pricing effect changes the rule on the fundamentals-based history and leaves the interaction separate. In Section 6.3, pricing instead changes on the baseline history, and the final step includes general-equilibrium price adjustment.

In the TFP experiment, the wage follows the counterfactual's recession path and the lending spread stays at its stationary value. The bank-capital experiment uses the counterfactual's wage and spread responses to the write-down. The third shock raises the lending spread while holding TFP and the wage fixed. Table D.4 also reports the debt-weighted default rate. After the bank-capital shock, current assessment-based pricing raises the headcount-weighted default-rate response while lowering the debt-weighted response at the benchmark persistence.

Table D.4: Decomposition of Responses for Every Shock and Wedge Persistence

	Fund.-based response	Total difference	Inherited distribution	Current pricing	Interaction
TFP shock, benchmark persistence					
Default rate (pp)	0.2712	−0.0062	+0.0053	−0.0110	−0.0006
		(−2.3%)	(+2.0%)	(−4.1%)	(−0.2%)
Debt-weighted default (pp)	0.1780	+0.0007	+0.0074	−0.0062	−0.0005
		(+0.4%)	(+4.1%)	(−3.5%)	(−0.3%)
Credit losses (bp)	15.89	+0.21	+0.76	−0.50	−0.04
		(+1.3%)	(+4.8%)	(−3.1%)	(−0.3%)
Investment (%)	−7.393	−0.006	−0.046	+0.038	+0.002
		(+0.1%)	(+0.6%)	(−0.5%)	(0.0%)
Output (%)	−9.904	+0.007	−0.025	+0.029	+0.003
		(−0.1%)	(+0.3%)	(−0.3%)	(0.0%)
Spread shock, benchmark persistence					
Default rate (pp)	0.1503	+0.0081	+0.0035	+0.0047	0.0000
		(+5.4%)	(+2.3%)	(+3.1%)	(0.0%)
Debt-weighted default (pp)	0.1138	+0.0031	+0.0047	−0.0019	+0.0002
		(+2.7%)	(+4.1%)	(−1.6%)	(+0.2%)
Credit losses (bp)	9.67	+0.35	+0.45	−0.14	+0.03
		(+3.6%)	(+4.6%)	(−1.4%)	(+0.3%)
Investment (%)	−10.745	−0.184	−0.011	−0.147	−0.027
		(+1.7%)	(+0.1%)	(+1.4%)	(+0.2%)
Output (%)	−3.963	−0.079	−0.006	−0.065	−0.008
		(+2.0%)	(+0.2%)	(+1.6%)	(+0.2%)
Bank-capital shock, benchmark persistence					
Default rate (pp)	0.0225	+0.0026	+0.0005	+0.0020	0.0000
		(+11.5%)	(+2.3%)	(+9.0%)	(+0.1%)
Debt-weighted default (pp)	0.0133	+0.0003	+0.0008	−0.0006	+0.0001
		(+2.2%)	(+5.8%)	(−4.5%)	(+0.8%)
Credit losses (bp)	1.07	+0.04	+0.07	−0.04	+0.01
		(+4.0%)	(+6.6%)	(−3.7%)	(+1.1%)
Investment (%)	−1.567	−0.102	+0.005	−0.097	−0.010
		(+6.5%)	(−0.3%)	(+6.2%)	(+0.6%)
Output (%)	−0.360	−0.046	+0.003	−0.045	−0.005
		(+12.9%)	(−0.9%)	(+12.4%)	(+1.3%)

Continued on the next page; notes follow the second part.

Table D.4: Decomposition of Responses (continued)

	Fund.-based response	Total difference	Inherited distribution	Current pricing	Interaction
TFP shock, $\rho_W = 0.5$					
Default rate (pp)	0.2712	−0.0051	+0.0040	−0.0091	−0.0001
		(−1.9%)	(+1.5%)	(−3.3%)	(0.0%)
Debt-weighted default (pp)	0.1780	+0.0011	+0.0067	−0.0055	−0.0001
		(+0.6%)	(+3.7%)	(−3.1%)	(0.0%)
Credit losses (bp)	15.89	+0.37	+0.79	−0.41	−0.01
		(+2.3%)	(+5.0%)	(−2.6%)	(0.0%)
Investment (%)	−7.393	−0.021	−0.054	+0.034	−0.001
		(+0.3%)	(+0.7%)	(−0.5%)	(0.0%)
Output (%)	−9.904	−0.021	−0.040	+0.019	0.000
		(+0.2%)	(+0.4%)	(−0.2%)	(0.0%)
Spread shock, $\rho_W = 0.5$					
Default rate (pp)	0.1503	+0.0079	+0.0034	+0.0045	0.0000
		(+5.3%)	(+2.3%)	(+3.0%)	(0.0%)
Debt-weighted default (pp)	0.1138	+0.0048	+0.0047	−0.0001	+0.0002
		(+4.2%)	(+4.2%)	(−0.1%)	(+0.2%)
Credit losses (bp)	9.67	+0.56	+0.54	0.00	+0.02
		(+5.8%)	(+5.6%)	(0.0%)	(+0.2%)
Investment (%)	−10.745	−0.174	−0.030	−0.145	+0.001
		(+1.6%)	(+0.3%)	(+1.4%)	(0.0%)
Output (%)	−3.963	−0.064	−0.007	−0.057	0.000
		(+1.6%)	(+0.2%)	(+1.4%)	(0.0%)
Bank-capital shock, $\rho_W = 0.5$					
Default rate (pp)	0.0225	+0.0021	+0.0005	+0.0016	+0.0001
		(+9.5%)	(+2.1%)	(+7.0%)	(+0.4%)
Debt-weighted default (pp)	0.0133	+0.0008	+0.0007	0.0000	+0.0001
		(+6.1%)	(+5.4%)	(0.0%)	(+0.7%)
Credit losses (bp)	1.07	+0.09	+0.08	0.00	+0.01
		(+8.4%)	(+7.7%)	(−0.3%)	(+0.9%)
Investment (%)	−1.567	−0.025	−0.006	−0.021	+0.002
		(+1.6%)	(+0.4%)	(+1.4%)	(−0.1%)
Output (%)	−0.360	−0.018	0.000	−0.018	0.000
		(+5.0%)	(+0.1%)	(+5.0%)	(−0.1%)

Notes: The decomposition follows (45), using common aggregate prices and firms present at date 0. Entrants are excluded. Each history and pricing rule uses its own no-shock path. The TFP shock lowers productivity by 5 percent. The wage follows the counterfactual's recession path and the lending spread stays at its stationary value. The bank-capital experiment uses the counterfactual's wage and spread paths after a write-down of 1 percent of bank assets. Responses sum years 0 to 10. Default-rate changes are percentage points and credit losses are basis points of the fundamentals-based book's initial credit. Investment and output are level changes divided by their fundamentals-based stationary levels, in percent-years. Parentheses give each component as a percentage of the fundamentals-based response. Debt-weighted default is each year's defaulted face-value debt divided by the debt of the initial cohort still present that year; annual shock-minus-no-shock changes are summed over years 0–10. The additional spread shock raises the lending spread by 100 basis points with persistence 0.8, while TFP and wages stay fixed.

Investment weights. Table D.5 shows how the inherited investment effect changes when high-risk firms receive a larger investment weight. Group responses and aggregate prices remain fixed.

Table D.5: Investment Weights

High-risk investment weight	Weight (%)	Additional decline (%)
Actual investment share	6.15	0.12
Share of bank loans	17.64	1.05
Share of additional losses	92.22	2.14
All investment	100.00	2.17

Notes. The TFP experiment in Section 6.3. Both histories use fundamentals-based pricing and common aggregate prices. Each row changes high-risk firms' investment weight while holding group responses fixed. The remaining weight goes to low-risk firms. Entrants are unchanged. Investment changes sum years 0 to 10 and use each group's initial investment in the fundamentals-based economy as the denominator. The additional decline is reported as a percentage of the reweighted fundamentals-based decline. High risk means a reference spread of at least 250.1 basis points.

Investment contributions. Table D.6 reports each group's contribution to the cumulative investment effect of current pricing. Initial firms and entrants together recover the current-pricing term in Table 6.2.

Table D.6: Contributions to Investment

Firm group	TFP shock	Bank-capital shock
Low risk, below-mean assessment	−0.0659	−0.0808
Low risk, mean assessment	−0.0309	−0.1013
Low risk, above-mean assessment	−0.0390	−0.0726
High risk, below-mean assessment	−0.0134	+0.0013
High risk, mean assessment	+0.0210	−0.0335
High risk, above-mean assessment	+0.0601	−0.0587
Entrants	+0.0039	−0.0133
Total	−0.0642	−0.3589

Notes. Contributions to the current-pricing effect in Section 6.3, summed over years 0 to 10 in percent-years. Experiments and group definitions follow Figure 6.3. Initial firms retain their date-0 groups, and entrants are reported separately. Contributions sum to the current-pricing term in Table 6.2. Negative values indicate a deeper investment decline. Totals use unrounded contributions.

E Technical Details

E.1 The Default Threshold

Fix the aggregate path, price schedule, and firm state. The investment financing set $\mathcal{A}_t(x)$ does not depend on m. A choice is feasible after the shock if $d_t^0(x, k', b') + m \geq 0$. Hence some choice is feasible if and only if $d_{\max,t}(x) + m \geq 0$. Because $V_{t+1} \geq 0$, every feasible choice yields non-negative value to equity. With repayment on ties, default is therefore exactly the event $m < -d_{\max,t}(x)$. Integrating over the normal cash-flow distribution gives (20). If the financing set itself is empty, I set $d_{\max,t} = -\infty$ and the default probability is one.

The shock is common to all choices available to a firm at a given date. It does not change their objective ranking when both choices are feasible, but it changes which choices are available. This is why the policy functions must be integrated over the shock as well as over persistent firm states. When σ_m approaches zero, the default probability converges to the hard feasibility rule away from the boundary.

E.2 Recovery, Entry, and Aggregation

Liquidating a firm with capital k produces $\xi(1-\delta)k$ units of the final good. Creditors receive $\min\{b, \xi(1-\delta)k\}$; any residual is transferred to the household. The firm has zero private continuation value on liquidation. This convention treats residual liquidation receipts as a household transfer, rather than an additional continuation payoff in (17). For debt pricing, recovery per unit is $r(k, b)$, with the harmless convention $r(k, 0) = 1$ when there is no debt to price.

An entrant receives capital k_e and face-value debt b_e, and draws (z, W) from a fixed entry distribution. The household finances the part of entry capital not covered by borrowing. If $q_t^e b_e$ is the value of one entrant's debt, then

$$S_t^E = \mathcal{E}_t q_t^e b_e, \qquad T_t^E = \mathcal{E}_t (k_e - q_t^e b_e). \tag{46}$$

Entrant debt is priced from its first operating-period repayment and recovery. There is no exogenous exit draw before the firm first enters. Thereafter the incumbent timing applies. Entry is exogenous; no free-entry condition is imposed.

Let $\mathcal{T}_t$ push the current firm distribution forward through repayment policies and the true transitions, integrating over m and discarding endogenous defaults. For a unit firm mass,

$$\mu_{t+1} = (1 - \pi_x)\mathcal{T}_t \mu_t + \mathcal{E}_t \mu^E, \qquad \mathcal{E}_t = 1 - (1 - \pi_x)\mathcal{M}_t, \tag{47}$$

where $\mathcal{M}_t = \int (1 - p_t^D(x)) d\mu_t(x)$ and μ^E is the entrant distribution. Exogenous exits have claims liquidated before their next operating period. All such payments enter CF at settlement.

Aggregate production includes output and the cash-flow endowment of operating firms:

$$Y_t = \int \int (1 - D_t(x, m))[y_t(z, k, \ell_t(z, k)) + m] \, dG_x(m) \, d\mu_t(x). \tag{48}$$

Although the unconditional cash-flow shock has mean zero, its mean among operating firms need not be zero because survival selects realizations. The same realized endowment must therefore enter both firm payouts and the resource account. Household liquidation receipts satisfy $\mathcal{L}_t^H = \mathcal{L}_t - \mathcal{L}_t^B$, where $\mathcal{L}_t$ is total liquidation resources and $\mathcal{L}_t^B$ is aggregate creditor recoveries. Substituting firm, intermediary, and household budgets cancels domestic financial flows and leaves (38) with the external payments in (37). Net payouts to foreign bank owners remain in the external account. The transfer $\mathcal{X}_t$ in the bank-capital experiment also enters that account and is deducted before banker turnover.

E.3 Intermediary Optimization and Leverage

This appendix derives the leverage condition for the adaptation of Gertler and Karadi (2011) in Section 3.4. Intermediaries hold long-term risky corporate debt and obtain foreign funding at the constant gross rate R^*. Bankers take aggregate prices as given, discount future payouts at the constant factor β_B, and evaluate portfolio returns using lenders' credit assessments. Following the initial aggregate shock, the aggregate path is deterministic. The derivation focuses on equilibria with positive intermediary net worth and a binding incentive constraint, between unanticipated bank-capital transfers. Such a transfer reduces inherited banker wealth before turnover, as in (29).

Individual balance sheets and timing. Consider banker j, who enters period t with net worth $n_{j,t}$. The banker purchases corporate claims with market value $a_{j,t}$ and borrows $a_{j,t} - n_{j,t}$ from foreign investors at the gross rate R^*. After receiving portfolio returns and repaying foreign borrowing, the banker's wealth is

$$n_{j,t+1} = R_{t+1}^B a_{j,t} - R^*(a_{j,t} - n_{j,t}). \tag{49}$$

Here R_{t+1}^B is the realized gross return on the corporate debt portfolio. Wealth $n_{j,t+1}$ is transferred to the foreign owner if the banker exits and remains in the bank if the banker continues operating.

Debt prices imply a perceived portfolio return of $\widetilde{\mathbb{E}}_t[R^B_{t+1}] = R^* + s_t$, where s_t is the common intermediation spread. Taking the subjective expectation of (49) gives

$$\widetilde{\mathbb{E}}_t[n_{j,t+1}] = R^* n_{j,t} + s_t a_{j,t}. \tag{50}$$

Holding net worth fixed, an additional unit of assets raises expected next-period wealth by s_t.

The banker's problem. Let $\mathcal{V}_t(n_{j,t})$ denote the value of operating a bank before choosing its asset holdings. A banker exits next period with probability $1 - \theta_B$ and transfers the remaining wealth to the owner. With probability θ_B, the banker continues operating. The value associated with current asset holdings is

$$\mathcal{J}_t(a_{j,t}, n_{j,t}) = \beta_B \widetilde{\mathbb{E}}_t \left[(1 - \theta_B) n_{j,t+1} + \theta_B \mathcal{V}_{t+1}(n_{j,t+1}) \right]. \tag{51}$$

Transfers from foreign owners to entering bankers provide their initial net worth and do not enter the incumbent banker's continuation problem.

After obtaining funding, the banker can divert a fraction λ_B of assets, forfeiting the value of continued operation. Creditors provide funding only when honoring the contract is at least as valuable as diversion. The banker therefore solves

$$\begin{aligned} \mathcal{V}_t(n_{j,t}) &= \max_{a_{j,t} \geq n_{j,t}} \mathcal{J}_t(a_{j,t}, n_{j,t}), \\ \text{subject to} \qquad & \mathcal{J}_t(a_{j,t}, n_{j,t}) \geq \lambda_B a_{j,t}. \end{aligned} \tag{52}$$

The restriction $a_{j,t} \geq n_{j,t}$ corresponds to nonnegative foreign borrowing.

For given aggregate prices, wealth accumulation and the incentive constraint are homogeneous of degree one in assets and net worth. Scaling current net worth and all asset choices by the same factor scales subsequent wealth and payouts by that factor. The value function consequently takes the form

$$\mathcal{V}_t(n_{j,t}) = \kappa^B_t n_{j,t}, \tag{53}$$

where κ^B_t is the value of a unit of net worth when the banker can optimally adjust lending. This coefficient is common across bankers because they face the same investment opportunities and incentive parameters.

Define the continuation multiplier

$$\Omega_{t+1} = 1 - \theta_B + \theta_B \kappa^B_{t+1}. \tag{54}$$

A unit of next-period wealth has value one upon exit and value κ_{t+1}^B in continued operation. The multiplier combines these values using the banker's survival probability.

Along the deterministic aggregate path, κ_{t+1}^B is known at date t. Substituting (50), (53), and (54) into (51) gives

$$\begin{aligned}\mathcal{J}_t(a_{j,t}, n_{j,t}) &= \beta_B \Omega_{t+1}(s_t a_{j,t} + R^* n_{j,t}) \\ &= \nu_t^B a_{j,t} + \eta_t^B n_{j,t},\end{aligned}$$

where

$$\nu_t^B = \beta_B \Omega_{t+1} s_t, \qquad \eta_t^B = \beta_B \Omega_{t+1} R^*. \tag{55}$$

The coefficient ν_t^B measures the value of expanding assets while holding net worth fixed. The coefficient η_t^B measures the value of replacing foreign borrowing with own funds while holding assets fixed. The optimized value of net worth, κ_t^B, also incorporates the adjustment of asset holdings.

The leverage limit. The incentive constraint can now be written as

$$(\lambda_B - \nu_t^B) a_{j,t} \leq \eta_t^B n_{j,t}. \tag{56}$$

Provided $\lambda_B > \nu_t^B$, it imposes the leverage limit

$$a_{j,t} \leq \phi_t n_{j,t}, \qquad \phi_t = \frac{\eta_t^B}{\lambda_B - \nu_t^B}. \tag{57}$$

When $s_t > 0$, (55) implies that the marginal value of assets is positive. The banker expands lending until the constraint binds and chooses $a_{j,t}^* = \phi_t n_{j,t}$. Evaluating the objective at this choice yields

$$\kappa_t^B = \eta_t^B + \nu_t^B \phi_t = \lambda_B \phi_t. \tag{58}$$

The final equality follows from the binding incentive constraint.

Substitution of (58) into (54) gives

$$\Omega_{t+1} = 1 - \theta_B + \theta_B \lambda_B \phi_{t+1}. \tag{59}$$

Combining (55), (57), and (59) yields

$$\phi_t = \frac{\beta_B R^* \left(1 - \theta_B + \theta_B \lambda_B \phi_{t+1}\right)}{\lambda_B - \beta_B s_t \left(1 - \theta_B + \theta_B \lambda_B \phi_{t+1}\right)}. \tag{60}$$

This is (31) in the main text. The coefficients ν_t^B, η_t^B, and Ω_{t+1} are determined by lending spreads and continuation values rather than calibrated independently.

Aggregation and credit-market clearing. Since all bankers face the same leverage limit, aggregation of their optimal asset holdings gives $S_t = \phi_t N_t^B$. Let μ_t be the distribution of firms entering the operating stage and G_x the conditional cash-flow distribution. The market value of corporate debt implied by firms' financing decisions is

$$S_t^F = \int \int (1 - D_t(x, m)) q_t(z, W, k_t', b_t') b_t' \, dG_x(m) \, d\mu_t(x) + S_t^E, \tag{61}$$

where policies depend on (x, m) and S_t^E is the market value of entrant debt defined in (46). The integral includes only firms that repay. Entrant loans are priced from their first operating-period payoffs, without an exit hazard before entry. Credit-market clearing requires $S_t = S_t^F$, and hence (32). The spread adjusts so that firms' debt demand equals intermediary lending capacity.

The binding solution requires $s_t > 0$, $\lambda_B - \nu_t^B > 0$, and $\phi_t \geq 1$. Equation (60) also uses the binding incentive constraint at the next date. Its application therefore requires the continuation path to remain in this regime. When $s_t = 0$, bankers are indifferent at the margin about expanding assets, and the capacity constraint need not bind. The credit-market conditions can be expressed as

$$s_t \geq 0, \qquad \phi_t N_t^B - S_t^F \geq 0, \qquad s_t(\phi_t N_t^B - S_t^F) = 0. \tag{62}$$

If the continuation path includes slack dates, the value coefficients must be evaluated from the banker's problem rather than imposing (58) at those dates.

Realized returns and aggregate net worth. Bankers' optimization uses perceived returns, while aggregate net worth evolves with realized returns. Summing (49) across incumbent bankers, retaining the wealth of those who continue operating, and adding capital supplied to entrants gives

$$N_{t+1}^B = \theta_B \left[R_{t+1}^B S_t - R^*(S_t - N_t^B) \right] + \omega_B S_t. \tag{63}$$

Equation (63) applies when $\mathcal{X}_{t+1} = 0$. In the bank-capital experiment, the transfer is deducted before banker turnover, as in (29). Thus, $n_{j,t+1}$ denotes an individual banker's wealth after debt repayment, whereas N_{t+1}^B includes the effects of banker exit and entry. To measure the difference between realized and perceived portfolio returns, define

$$R_{t+1}^B = (R^* + s_t)(1 + \delta_{t+1}^B). \tag{64}$$

The return surprise δ^B_{t+1} reflects repayment, recovery, and the valuation of surviving claims under the true transition law. The rating wedge can affect both perceived lending opportunities and realized portfolio returns. A known aggregate recovery path does not eliminate the difference between perceived and true productivity transitions.

Terminal conditions. For a transition computed over dates $0, \ldots, T-1$, the backward recursion uses

$$\phi_T = \bar{\phi}^{\,e}, \qquad e \in \{C, W\}, \tag{65}$$

where $\bar{\phi}^{\,e}$ is the leverage ratio in the stationary equilibrium approached by economy e. The fundamentals-based and assessment-based economies use their respective stationary values, with common intermediary parameters.

Given a candidate spread path, (60) determines leverage limits backward from the terminal condition. Realized returns and aggregate net worth are evaluated forward from inherited asset holdings and foreign liabilities. In particular, the initial aggregate shock revalues the inherited portfolio and therefore affects current bank net worth. Equilibrium spreads make the resulting lending capacities consistent with firms' debt choices at every date.

The terminal stationary allocation must satisfy both the incentive constraint and net-worth accumulation:

$$\begin{aligned} \lambda_B \bar{\phi}^{\,e} &= \beta_B \left(1 - \theta_B + \theta_B \lambda_B \bar{\phi}^{\,e}\right) \left(R^* + \bar{s}^{\,e} \bar{\phi}^{\,e}\right), \\ 1 &= \theta_B \left[R^* + (\bar{R}^{B,e} - R^*) \bar{\phi}^{\,e}\right] + \omega_B \bar{\phi}^{\,e}. \end{aligned} \tag{66}$$

The first condition uses perceived lending returns; the second uses the realized stationary return $\bar{R}^{B,e}$. These returns coincide in the fundamentals-based stationary economy. They need not coincide when debt prices reflect distorted credit assessments.

I select the finite-value stationary continuation. With a diversified portfolio, the perceived gross growth rate of an incumbent banker's wealth is $R^* + \bar{s}^{\,e} \bar{\phi}^{\,e}$. A sufficient condition for discounted expected payouts to remain finite is

$$\beta_B \theta_B \left(R^* + \bar{s}^{\,e} \bar{\phi}^{\,e}\right) < 1. \tag{67}$$

Under this condition, the stationary continuation multiplier satisfies

$$\bar{\Omega}^{\,e} = \frac{1 - \theta_B}{1 - \beta_B \theta_B \left(R^* + \bar{s}^{\,e} \bar{\phi}^{\,e}\right)}.$$

The terminal condition in (65) approximates this stationary continuation beyond the numerical horizon.

E.4 Stationary Intermediary Parameters

In the fundamentals-based stationary economy, the true and perceived returns coincide. Given $\bar{s}_C$, $\bar{\phi}_C$, θ_B, and R^*, define

$$\begin{aligned}\bar{\Omega} &= \frac{1-\theta_B}{1-\theta_B\beta_B(R^*+\bar{\phi}_C\bar{s}_C)},\\ \lambda_B &= \beta_B\bar{\Omega}\left(\bar{s}_C+\frac{R^*}{\bar{\phi}_C}\right),\\ \omega_B &= \frac{1-\theta_B(R^*+\bar{\phi}_C\bar{s}_C)}{\bar{\phi}_C}.\end{aligned} \tag{68}$$

The parameterization requires positive denominators and $\omega_B \geq 0$. For $(\bar{s}_C, \bar{\phi}_C, \theta_B, R^*) = (0.01, 10, 0.80, 1.03)$ and $\beta_B = 1/R^*$, it gives $\bar{\Omega} = 1.63492$, $\lambda_B = 0.17937$, and $\omega_B = 0.00960$.

The assessment-based economy retains these parameters. Its stationary return surprise $\bar{\delta}^B$ is an outcome of the firm distribution and pricing rule. In the binding region, stationary net-worth accumulation implies

$$\bar{\phi}_W = \frac{1-\theta_B R^*}{\theta_B[(R^*+\bar{s}_W)(1+\bar{\delta}^B)-R^*]+\omega_B}. \tag{69}$$

This condition holds jointly with the intermediary's incentive constraint, firm optimization, and labor-market clearing. Both economies use the same household preference parameters. Stationary wages, spreads, and leverage adjust across economies.

E.5 Solution and Accounting Checks

I discretize productivity and the rating wedge and solve the firm's problem on grids for capital and debt. Conditional default probabilities use the normal distribution in (20). Repayment policies are integrated across cash-flow intervals, including the probability mass and conditional shock mean in each interval. Firms' continuation values use the true productivity transition; debt prices use the perceived one. Stationary values, prices, policies, and the invariant distribution are iterated jointly conditional on aggregate prices. I solve the baseline stationary equilibrium jointly with the hours target used to calibrate χ. Labor and credit markets determine the stationary wage and spread. The household's labor-supply condition determines χ. I then solve the fundamentals-based pricing equilibrium with the same χ.

For the deterministic transition, I impose the corresponding stationary equilibrium at a distant terminal date. Given candidate wage and spread paths, I solve firm values and prices backward and move the distribution forward. Realized loan returns determine net

worth forward, while the intermediary value recursions determine leverage backward. Updating wages and spreads reduces the labor-market and credit-market residuals. The common-price steps in Section 6.3 take both price paths as given and solve only firms' decisions and the distribution path. The final step uses the baseline economy's own general-equilibrium paths.

The accounting checks compare the direct valuation of inherited loan payoffs with (28); verify intermediary net-worth accumulation; and compare household consumption with the aggregate resource identity. Numerical checks also include no-shock stationarity, positive consumption and net worth, and the sign and slack conditions in (62). Removing the belief distortion must make the two productivity expectation operators coincide. Setting $\omega_I = 0$ must remove the investment-financing restriction.

The reference calculations use 45 productivity states, 5 wedge states when the wedge is active, 60 points each for capital and debt, and 15 cash-flow intervals. Transition comparisons use horizons of 100 and 200 years, with reported cumulative effects over years 0–10. An equilibrium residual target of 10^{-5} is complemented by accounting checks and comparisons across initial guesses and terminal horizons. The variation across such solutions is reported as numerical sensitivity, not as a proven error bound. Small reported effects require particular care relative to this sensitivity.

E.6 Additional Comparisons

The persistence comparison in Appendix C changes how quickly the assessment advantage fades. The wedge grid and the stationary variance of the continuous AR(1) process are held fixed, with the innovation variance adjusted as persistence changes. Discretization need not preserve exactly the same stationary variance of the finite-state chain. Each specification uses its own stationary firm distribution. The financing comparison in Appendix B changes the required investment-financing share and recalibrates the fixed operating cost to preserve the incumbent default target.

The general-equilibrium comparisons hold household preferences and bank technology fixed across the baseline and fundamentals-based pricing economies. The fixed-price decompositions impose common wage and spread paths across the cases being compared.