Discussion of Three Papers Assessing Credit Risk

by

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General Remarks on Credit Risk

► There are various commonly-used definitions of credit risk, such as:

1. Probability of default (e.g., Standard & Poor’s)
2. Expected default losses (e.g., Moody’s, Fitch)
3. Expected default losses plus systematic default risk premia (e.g., debt credit spreads)

► Even using the same definition, agents’ credit risk evaluations may differ due to:

1. Moral hazard biases (e.g., intentionally inflating ratings)
2. Psychological biases (e.g., irrational risk salience)
3. Differences in information (e.g., limited reporting of relevant information)

► This session’s three papers analyze reasons why credit risk evaluations differ.
Agent banks and examiners categorize large syndicated loans into 5 ratings:

1. **Pass**: in good standing and not criticized by supervisors. 86.9% obs.
2. **Special Mention**: has potential weaknesses that deserves mgt attention. 4.5% obs.
3. **Substandard**: inadequately protected by obligor paying capacity or collateral. 6.4% obs.
4. **Doubtful**: weaknesses make full collection questionable or improbable. 1.1% obs.
5. **Loss**: loan amounts should be promptly charged off. 1.1% obs.

This paper models loan rating changes and also compares ratings assigned by an agent bank to those assigned shortly after by a bank regulator that randomly examines loans.
Prior research used similar models to forecast bond credit rating changes:

- Are rating change probabilities likely to be constant over the business cycle?

The paper finds evidence that examiners’ ratings tend to be worse than those previously assigned by banks, consistent with banks “inflating” their ratings.

- But if examiners know the bank’s prior rating, might examiners have a bias against assigning a better rating due to bank private information or regulatory reputation?
- Also, since 87% of loans cluster at the highest rating of “pass,” most rational disagreements between banks and examiners can only result in a worse examiner rating.

I find the paper’s results on spillovers to be very credible:

- Examiners’ rating of a loan reflects their preferences and information that a rational bank should use to revise its ratings of other similar (e.g., same industry) loans.
Regulatory Risk Perception and Small Business Lending
by Joseph Kalmenovitz and Siddharth Vij

This paper uses 1998-2019 data on the SBA’s employees and loans to show:

1. Current defaults on loans guaranteed from offices where SBA employees previously worked reduce same-industry loan guarantees at these employees’ current office.
2. As a result, loan defaults, the number of new small firms, and job creation decline in the county of the current office.
3. The effect is greater when the employees’ current office is smaller, decisions are decentralized, and employee compensation is not performance-based.

The paper’s results are intriguing and robust to several different test specifications.
Prior research has found that employees’ prior experiences affects their decisions. But the current paper finds that current events at employees’ old offices, which may be thousands of miles away, affect their decisions at their new office.

Might another explanation be that employees specialize in particular industries and continue to have some responsibility for their prior work at their old office? They may need to explain why they guaranteed defaulted loans and assist workouts. Current defaults on their prior loans reduce their productivity in processing loan applications at their new office, especially if decisions are made at small offices.

If compensation is based on volume-based performance measures, that might explain why it ameliorates the reduction in guarantees.
Can Credit Rating Affect Credit Risk? Causal Evidence from an Online Lending Marketplace by Amiyatosh Purnanandam and Alexander Wirth

Due to the CARES Act, control (treated) borrowers entering a LC hardship plan before (after) Feb 1, 2020 were (were not) reported as paying late to credit bureaus.

1. Treated borrowers had relatively higher post-hardship FICO scores.
2. Treated borrowers had relatively lower post-hardship cumulative default rates.
3. Treated borrowers had relatively higher post-hardship loan repayment rates.

Among the paper’s conclusion are:

1. Exogenously raising credit scores raises borrower performance and reduces default.
2. Credit bureau reporting errors that reduce credit scores can be costly.
The paper’s test design is clever.

One interpretation of the CARES Act was that it required a credit bureau reporting error that favored treated borrowers.

- With the loss of reporting information, treated borrowers were “pooled” with better-quality, non-hardship ones by being assigned the same FICO score.
- Lenders that recognize this pooling may reduce, or increase the cost of, credit to the pool of same-FICO borrowers, including the better-quality ones.
- Effectively, the better-quality pooled borrowers cross-subsidize new credit for the treated ones who then will default less relative to control borrowers.
- The welfare effects are unclear since if enough late-payment borrowers are unreported, lenders may cease credit to all borrowers (a “lemons” market).
Several of the paper’s tests, including cross-section tests, are set in “event time,” i.e., a comparison of behavior before versus after entering hardship.

The before vs after Feb 1 date may matter beyond reporting vs not reporting.

Since the treatment period extended from Feb 1 to “early” March, the decision to seek hardship may have been influenced by COVID news that began in late February.

Perhaps more importantly, CARES Act stimulus checks paid on April 11-15 were received sooner in event time by treated borrowers which (with a 2-3 month delay) may have improved their FICO scores and repayment capacity more.

The effect of receiving government aid earlier may have significantly lowered default rates since consumer bankruptcy rates declined substantially in 2020.*

Corporate bond credit spreads began rising in late February 2020.
To alleviate the effects of confounding events, the paper might consider a shorter sample interval, e.g., control group are those entering hardship only in Jan 2020 vs treated group are those entering hardship only in Feb 2020.
Conclusions

► These three papers highlight important reasons why banks’, bank regulators’, and government loan guarantors’ credit evaluations may differ.

► The economic consequences of these credit evaluation differences may be substantial.