Information Noise and Credit Risk: Evidence from Corporate Bankruptcy

Credit Scoring and Credit Control Conference XV

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Paper In A Nutshell

- Current practice in bankruptcy/default prediction

$$log(\lambda_t) = \beta' X_t \quad \text{or} \quad logit(\lambda_t) = \beta' X_t$$

  where λ_t is hazard rate, X_t is time-varying covariates, β is coefficients
- When there is information noise in input data, theory of Duffie and Lando [2001] (DL) implies RHS should be nonlinear and approximated by **interaction effects**
- Empirical implications of those **noise-induced interactions**
  - Existence of the interactions and improvements in Goodness-of-Fit
  - Improved out-of-sample forecasting accuracy of models augmented by the interactions
  - Insights into "Are larger, or more transparent, firms less likely to fail? Are they more predictable?"
  - Reconciliation of puzzling empirical results in the literature
- Using over two million firm-months panel of North American firms during 1979-2012, we demonstrate the existence of the interactions, and strong evidence supporting their implications

Theory

Problem

- There is a noise in the accounting reports of a debt issuer (firm), which is
  - Associated with log(asset)
  - Normally distributed, $\sim\mathcal{N}(u, a^2)$ *
- Only noisy value of assets is observed by creditors/modellers
- Firm files bankruptcy (or defaults) when true log(asset) first falls below a low boundary, $\underline{v}$
- $\boldsymbol{a}$ **is "a measure of the degree of noise"** (DL)

Solution

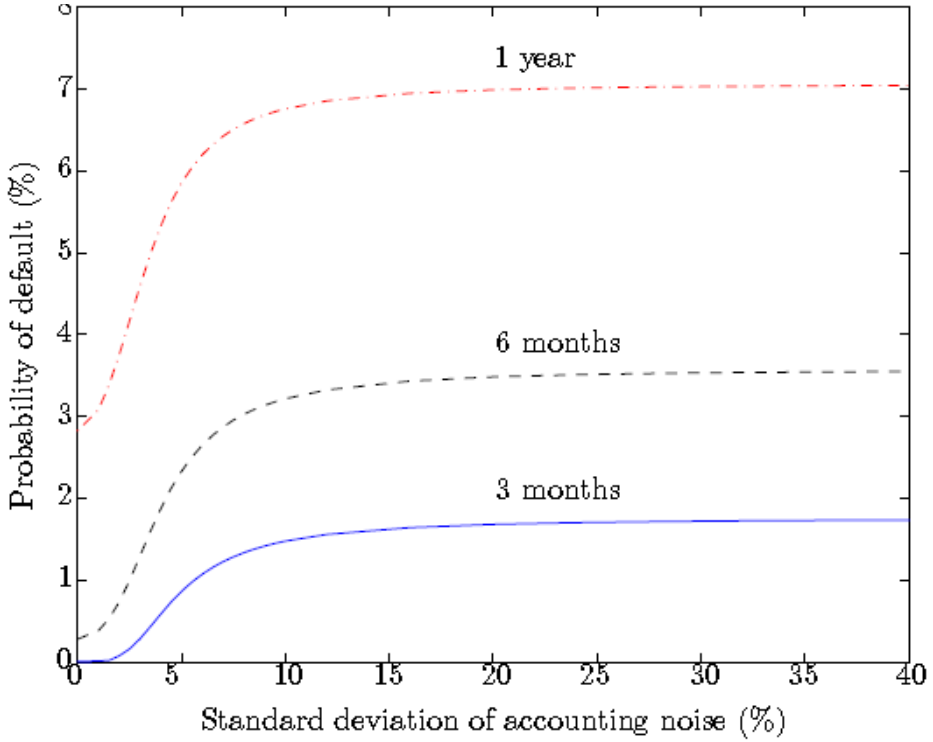
- A filtering problem: Conditional on the observed (noisy) asset value, what is the **conditional Probability of Bankruptcy/Default** (PB/PD)?
- DL provided an analytical solution to this problem
- What does the theoretical PB/PD look like?

* We assume unbiased accounting reports ($u = -\frac{a^2}{2}$) throughout the paper

Two Dimensions, PB-a

The plot when the observed (noisy) asset growth rate is **0**

- Is this the whole picture? What happens if the observed (noisy) asset growth rate is non-zero?
- Is (1-year) PB/PD always increasing in a?

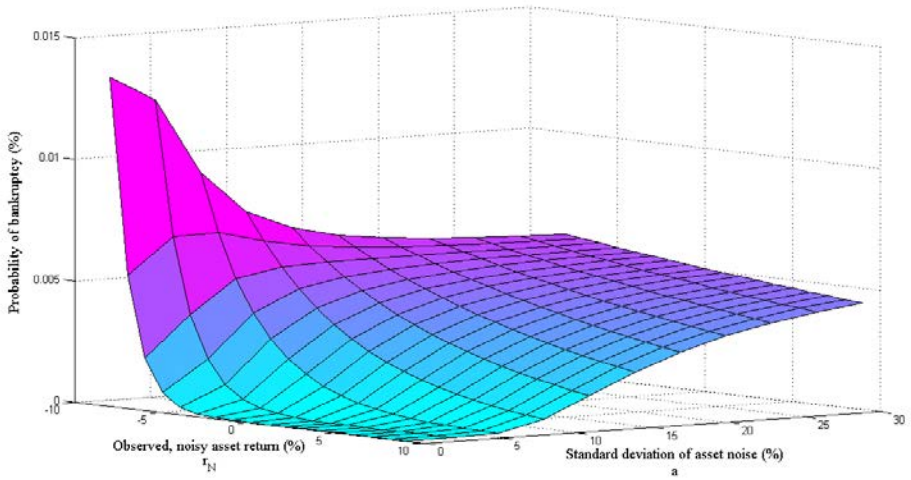


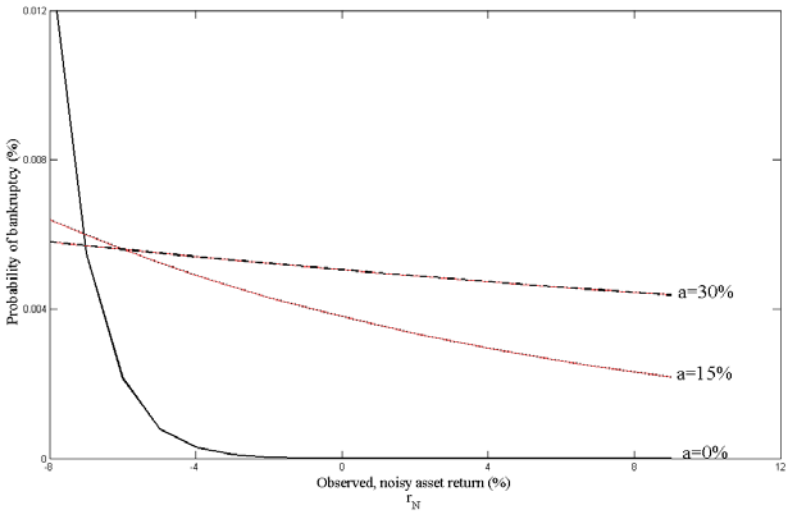
Source: Figure 4 in Duffie and Lando [2001, Econometrica], with permissions from Econometrica and the authors

Three Dimensions, PB-a-r_N

Bayes rule: the higher degree of noise, the less responsiveness of observed asset growth rate to PB/PD, and vice versa

Similar patterns for any monotonic transformation (e.g. log or logit) of PB/PD





Plot on PB-a-r_N and projections on PB-r_N

Testable Hypotheses (1/2)

PB can be approximated by hazard rate (see DL for existence of the limit)

$$\lambda_t = \lim_{\Delta t \to 0} \frac{PB(t, t+\Delta t)}{\Delta t}$$

- **Hypothesis 1** (Existence of the noise-induced interaction effects):
  (i) We can explicitly predict the sign of coefficients on interaction effects, $\bar{\gamma}_i$
  (ii) Improved Goodness-of-Fit

$$\log(\lambda_t) = \bar{\beta}' X_t + \bar{\gamma}_0 \tilde{a} + \sum_{i=1}^{I} \bar{\gamma}_i \left(\tilde{a} * X^i\right)$$

  - Without loss of generality, $\tilde{a}$ is a proxy for the degree of noise, **such that $\tilde{a}$ is decreasing in a**
  - If X^i is increasing in λ_t, then $\bar{\gamma}_i > 0$
  - If X^i is decreasing in λ_t, then $\bar{\gamma}_i < 0$
- Example:
  - **Observed (noisy) asset return** is **decreasing** in λ_t
  - When interacting it with **firm size** (a proxy that is decreasing in a), the interaction effect should have a **negative** coefficient

Testable Hypotheses (2/2)

- **Hypothesis 2** (Out-of-Sample Forecasting Accuracy): Out-of-sample forecasting accuracy is improved by models augmented by the interactions, compared to those without

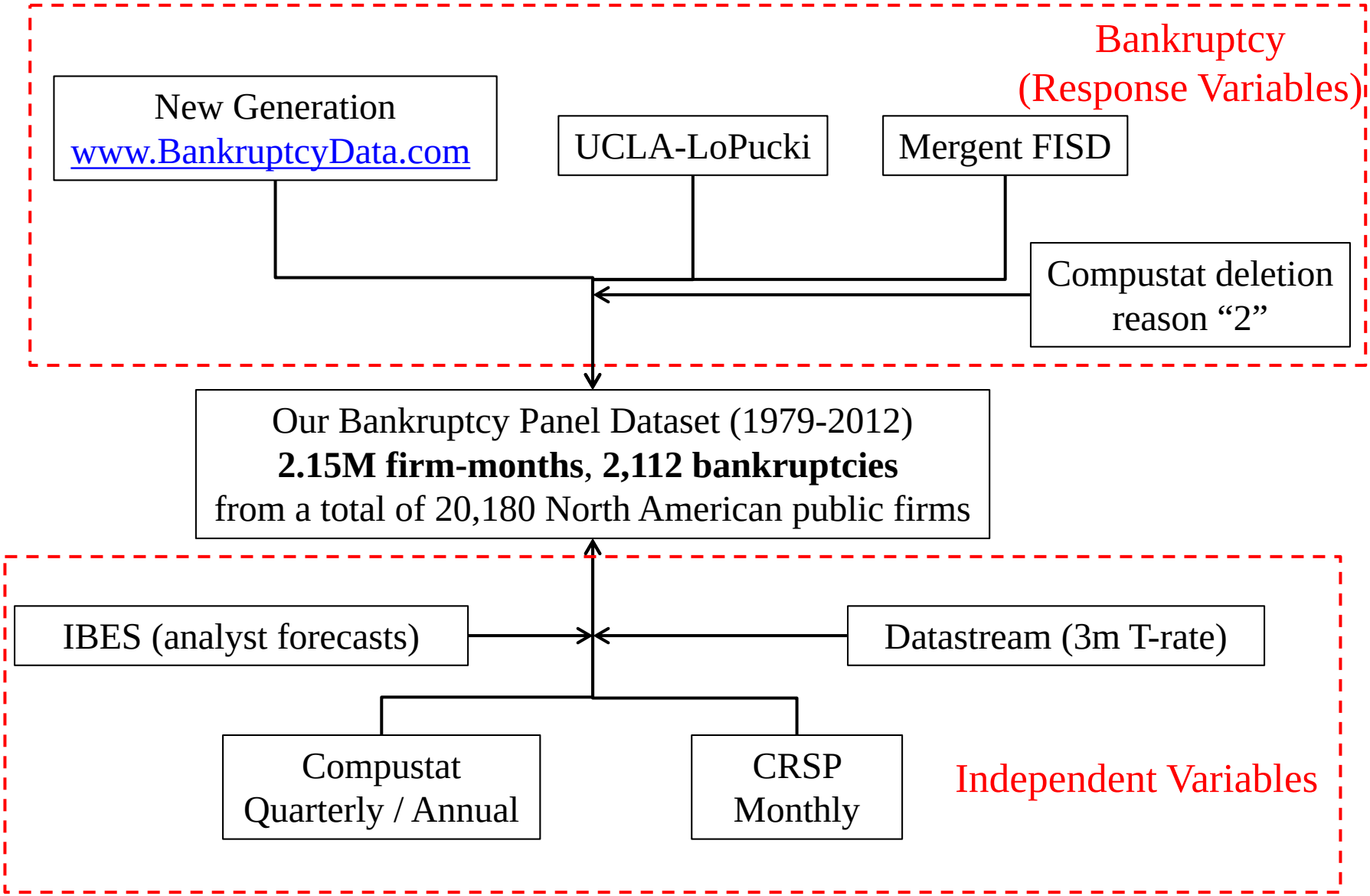
- **Hypothesis 3** (Relation of the degree of noise to credit risk and predictability):
  - Are larger, or more transparent, firms less likely to fail? NO
  - Are they more predictable? YES

- **Hypothesis 4**:(Reconciliation of the puzzling empirical findings about RSIZE and NI/TA): In hazard models estimated from different types of firms, the partial effects of RSIZE may have different signs, and the significance of NI/TA's partial effects may vary, all else equal.

Empirical Design

- This paper uses Cox [1972] Proportional Hazard Model to model hazard rate λ_t
- Identify time-varying covariates, X_t
  - From well-known, well-accepted models (reference models) in the literature
  - Main results: Shumway [2001, JoB] (S01 Model)
  - Robustness checks
    - Chava and Jarrow [2004, RoF] (CJ04 Model)
    - Simplified version of Duffie, Saita and Wang [2007, JFE] (DSW07-S Model)
    - Bharath and Shumway [2008, RFS] (BS08 Model)
- Proxy for the degree of noise, $\tilde{a}$, that is decreasing in a
  - Well-accepted proxies from the Finance literature
  - Absolute firm size: log[Total Assets] (log(TA)), log[Equity] (logE)
  - Relative firm size: log[Asset Rank] (log(AR)), RISZE from S01 Model
  - Analyst coverage (AC)
  - Analysts' forecast variation (-log(CV))

Data


Bankruptcy
(Response Variables)
New Generation
www.BankruptcyData.com
UCLA-LoPucki
Mergent FISD
Compustat deletion
reason "2"
Our Bankruptcy Panel Dataset (1979-2012)
2.15M firm-months, 2,112 bankruptcies
from a total of 20,180 North American public firms
IBES (analyst forecasts)
Datastream (3m T-rate)
Compustat
Quarterly / Annual
CRSP
Monthly
Independent Variables

Empirical Results (1/3)

SSRN: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=2347079)

Conclusions (details in paper)

- Hypothesis 1: Existence of interactions by in-sample tests
  - The signs of coefficients on the interaction effects are consistent with the hypothesis
  - Likelihood Ratio tests and AIC demonstrate significant improvements in Goodness-of-Fit
- Hypothesis 2: Out-of-sample forecasting accuracy in the 10-year holdout periods
  - Main results: measured by Area Under ROC Curve (AUC) and using all the proxies for *a*, the interactions bring notable AUC uplifts, in both statistical significance and economic magnitude
    - Scenario 1: data is not winsorized
    - Scenario 2: data is winsorized
    - Scenario 3: information is noisier, i.e., less frequently updated financial reporting, no stock market information, fewer covariates, more outliers
  - Robustness checks: confirmed improvements by another measure, “captured bankruptcies within deciles”

Empirical Results (2/3)

- Hypothesis 3: Relations of the degree of noise to hazard rate and predictability
  - When firms' return-related variables (NI/TA or EXRET) are "substantially negative", **higher firm size robustly entails higher hazard rate**, contrasting with common intuitions (e.g. Shumway [2001])

    Similar results are obtained using other proxies for the degree of noise, implying **more transparent firms entail higher credit risk**. This is in contrast with discretionary disclosure theories (e.g. references in Yu [2005])
  - The above relations are **inverted** when firms' return-related variables become less negative or positive
  - Demonstrated using all the proxies, a single model has higher discriminative power (out-of-sample AUC) in sub-sample with lower degree of noise
- Hypothesis 4: Reconciliation of puzzling empirical results
  - Contradictory empirical findings in the literature about the sign of partial effects of RSIZE, and significance of NI/TA
  - Controlling for sample periods and model specifications, we replicate the findings in different MECE segments of a single dataset, and attribute them to the interactions

Empirical Results (3/3)

- Robustness checks
  - Find very similar results in **sub-periods**
  - Re-run all the tests based on **three alternative reference models**, and obtain similar results, both quantitatively and qualitatively
  - Confirm that the out-of-sample results are robust to **different sample sizes**
  - Test all the hypotheses based on **non-financial firms**, and draw the same conclusions
  - Examine and confirm out-of-sample results based on an **alternative measure of forecasting accuracy**
    - Augmented models capture more bankruptcies in top 2 or 3 deciles, with CAP curve being no lower than that of reference models in all deciles
    - Within the low-risk deciles, augmented models capture notably less bankruptcies, leading to less potential misclassification
  - Re-run the empirical tests and find qualitatively similar results, relating to the proxies AC and -log(CV), by **imputing the missing values** and including firms with no IBES information

Contributions

- New tests on DL theory from the perspective of PD/PB, which are cleaner and more straightforward
- Contributions to the literature of corporate bankruptcy/default prediction
  - Introduce new and simple ways of taking into account information noise, which improve hazard models' empirical performance
  - Shed light on the causal effects of the covariates that lead to inconsistent empirical findings
- Highlighting the importance of the noise-induced interactions in empirical research, by demonstrating that intuitions without considering the interactions' implications may lead to spurious conclusions
- New insights into the predictability of credit risk, offering an interesting perspective and deeper understanding on the causal effects of predictability
- Industry applications on credit rating models: applicable to improving the accuracy and robustness of PD models

Future Work

This paper opens a number of opportunities for future empirical research

- A starting point to study the complicated relations of credit risk to asset pricing, induced by information quality
- Approaches to investigate the degree of information transparency and asymmetry, between creditors and firms, and its impact on credit spreads and credit markets
- Study of different forms of incomplete information, like biased accounting reports or delayed information, or different proxies for the degree of noise
- Tests using default events and for general firm types (e.g. non-public firms)

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