Discussion of: "Exploring the sources of loan default clustering using survival analysis with frailty"

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Summary

- The paper documents that models with grouped frailty outperform models without frailty for the modeling of loan credit risk of SME's
  - When frailties are grouped by the systemic importance of issuing bank
  - After accounting for loan, firm, and macro variables
  - Especially for the smallest Mexican firms
- It proposes an approach to construct internally consistent estimates of conditional default probabilities over multiple periods

My take

- The paper provides further evidence of the relevance of frailty, especially for smaller firms
- It uses an alternative modeling approach, providing validation to existing literature
- My comments will focus primarily on the contribution to literature
  - Where does the literature stand right now?
  - How does the paper fit in?
  - Open questions

Broader picture

- Credit risk modeling goes back a long way!
  - Altman (1968) already used hazard-like models to establish the relevance of firm-specific variables for credit risk
- Clustering in default times was observed early already as well
  - Lang and Stulz (1992) documented clustering of defaults within industries
- Big progress was made by Das et al. (2007)
  - Rejected the null hypothesis that firm default times are **conditionally independent**; i.e., that they are correlated just through exogenous firm & macro risk factors
- Duffie et al. (2009) introduced the concept of **frailty** to capture the excess default clustering in U.S. data

Pre Duffie et al. (2009)

- Suppose that T_i is the default time of Entity i (which may be a firm or a loan, more on this later)
- Most models prior to Duffie et al. (2009) assumed that the survival function of Entity i is

$$S_i(t) = \mathbb{P}_t\left(T_i > t\right) = \exp\left(-\int_0^t \lambda_{i,s} \mathrm{d}s\right),$$

  where $\lambda_{i,s}$ is the intensity (i.e., the conditional default rate; the higher $\lambda_{s,i}$, the more likely that Entity i will default early)
- Typically, λ_s is assumed to be a function of a vector of observable firm variables $X_{i,s}$ and macro variables Y_s:

$$\lambda_{i,s} = f(X_{i,s}, Y_s)$$

- This specification was rejected by Das et al. (2007)

Post Duffie et al. (2009)

- What Duffie et al. (2009) did is to introduce a **latent** factor that is common across all entities and drives excess default correlation:
  - In particular, Duffie et al. (2009) assume that the default intensity is
  $$\lambda_{i,s} = f(X_{i,s}, Y_s, Z_s),$$
  where Z is not latent
- Initially, frailty was mostly a statistical artifact
  - Z can be viewed as a residual, capturing any default correlation that cannot be explained by observable factors
- More recently, frailty is understood to capture **information contagion** (Koopman et al. (2011), Benzoni et al. (2015))
  - Investors extrapolate financial distress across firms, affecting the financing options of surviving firms

Where is the literature now?

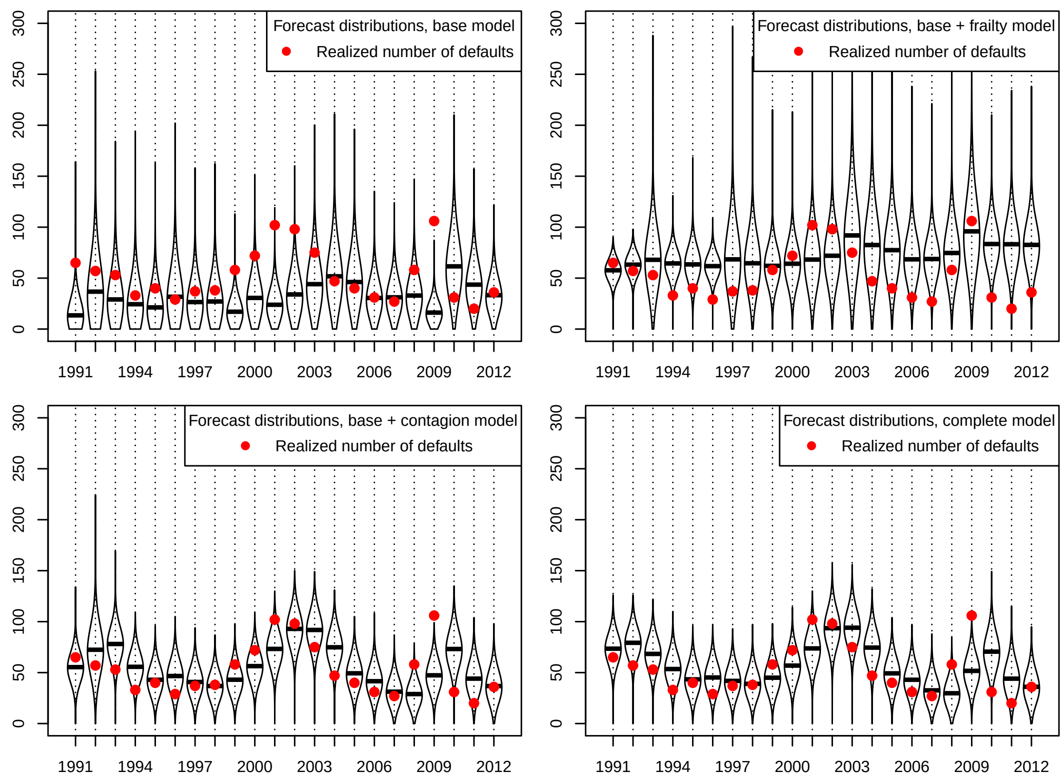
- Most recently, Azizpour et al. (2018) reject the null hypothesis that the frailty formulation of Duffie et al. (2009) is sufficient to explain the degree of default correlation in U.S. data
  - Instead, we show that a specification of the type

$$\lambda_{i,s} = f(X_{i,s}, Y_s, Z_s, T_{-i}),$$

    where T_{-i} are the default times of all other firms, **cannot** be rejected by the data

- The results of Azizpour et al. (2018) highlight **network effects**
  - Cascades of failures among interconnected firms, as in Acemoglu et al. (2012), Eisenberg and Noe (2001), and others
- Both network and frailty channels are critical

Models without frailty or contagion



Azizpour et al. (2018) establish that models that neglect frailty tends to understate credit risk out-of-sample, while models that neglect network effects generate too dispersed credit risk forecasts

How the paper fit in the literature?

- The paper assumes the following specification

$$\lambda_{i,s} = f(X_{i,s}, Y_s, Z_{\text{Group}(i)}),$$

where T_{-i} are the default times of all other firms, cannot be rejected by the data

- Compared to the specification of Azizpour et al. (2018):

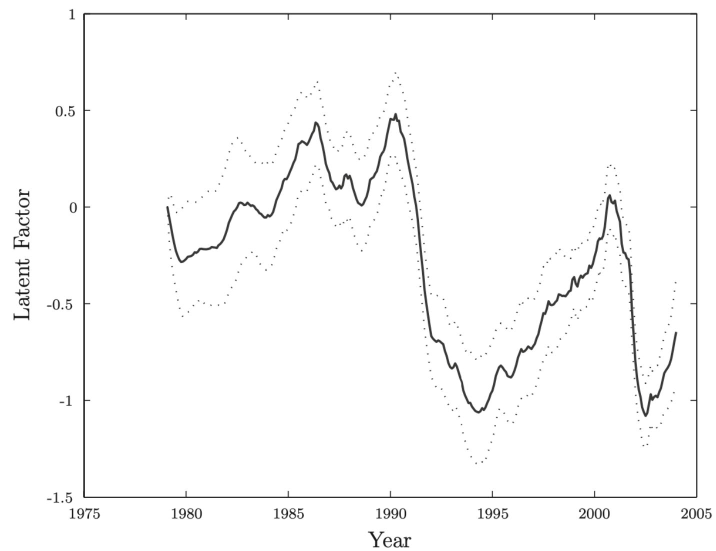
$$\lambda_{i,s} = f(X_{i,s}, Y_s, Z_s, T_{-i})$$

- The paper focuses on loan defaults while Azizpour et al. (2018) focuses on firm failures

- What consequences might these differing approaches have?

Frailty choices

- The frailty model of the paper is more granular but less dynamic than the one of Azizpour et al. (2018)
  - Time-variation appears to be critical



Posterior mean of frailty of Duffie et al. (2009)

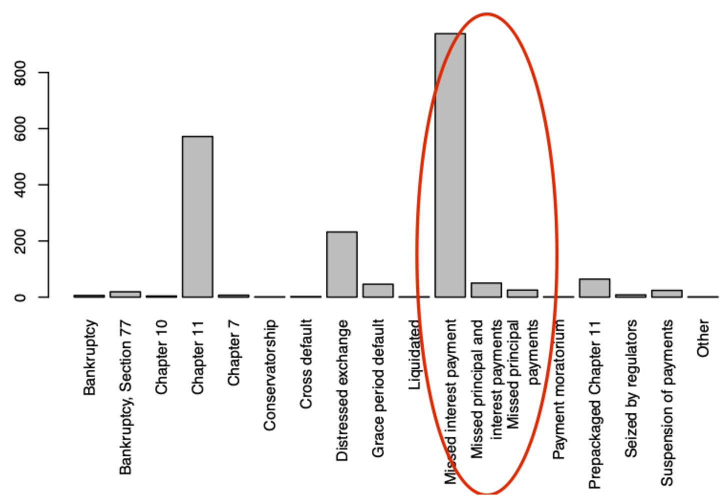
  - Granularity also appears important (Chava et al. (2011))
- Open question: interaction of frailty granularity & time variation?

Neglecting the network channel

- The paper neglects the network channel of contagion
- But the network channel of credit risk appears to be critical
  - Azizpour et al. (2018) reject all models that do not include network effects
- Open question: to which degree does a more granular frailty capture network effects?
  - Data on network interconnections is hard to get, but critical for loan-level modeling (see Schwenkler and Zheng (2019) for a recent attempt at extracting network data from the news).

Loan vs firm defaults

- The authors argue that they differ from the literature because they study loan-level credit risk rather than firm credit risk
- But most papers in this space consider several types of defaults besides Chapter 7 & Chapter 11. Some of them coincide with the definition of default of the paper!



Types of defaults in Azizpour et al. (2018)

- These types of events are considered to be defaults by Moody's

Loan vs firm defaults

- Most existing papers exclude subsequent events of this type within a certain time frame (1 year)
- This is because, once the rating agency has assigned a default label to a firm, it causes all sorts of issues for its financing options
- But the paper considers the study of the clustering of many of these events for the same firm to be main contribution
  - Can the authors flesh out more clearly why this would lead to different insights?
- It may be that many of these SME loans are not rated, so that loan-level modeling may be more relevant than firm-level modeling
  - Is this then more a study of rated vs non-rated bonds?

Minor comments

- Hazard $\neq$ intensity
  - Actually, hazard $=$ posterior mean of intensity under an equivalent probability measure (see Giesecke and Schwenkler (2018))
  - Interpretation of estimates?
- Internally consistent multi-period default probability forecasting also possible for reduced form models as in Azizpour et al. (2018)
- Christoffersen and Matin (2019) introduce a machine-learning credit risk model with multivariate frailties, similar to the approach in the paper

Conclusion

- New evidence in support of frailty in an interesting context!
- The paper contributes to a rich existing literature
- The authors can push their paper a bit further, fleshing out their contributions relative to the field
- Good luck with the paper!

Thank you!

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