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Unobserved systematic risk factor and default prediction ☆

Min Qi [a,*], Xiaofei Zhang [b], Xinlei Zhao [a]

[a] *Credit Risk Analysis Division, Office of the Comptroller of the Currency, United States*
[b] *Market Risk Analysis Division, Office of the Comptroller of the Currency, United States*

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ABSTRACT

We conduct a thorough analysis on the role played by the unobserved systematic risk factor in default prediction. We find that this latent factor outweighs the observed systematic risk factors and can substantially improve the in-sample predictive accuracy at the firm, rating group, and aggregate levels. Thus it might be helpful to include the unobserved systematic risk factor when simulating portfolio credit losses. However, we also find that this factor only marginally improves out-of-sample model performance. Therefore, although the models we investigated all show reasonably good ability to rank order firms by default risk, accurate prediction of default rate remains challenging even when the unobserved systematic risk factor is considered.

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1. Introduction

Probability of default (PD) is likely the most prominent component of credit risk analysis. PD is also one of the main parameters in the Basel II framework that are used to calculate banks' regulatory capital requirements. Because of its importance, much effort has been devoted to the development of default prediction models.[1] However, accurate prediction of default probability remains difficult (see Shumway (2001), Huang and Huang (2002) and Bharath and Shumway (2008)).

Recent credit risk literature indicates that observed macroeconomic variables and firm-level information are not sufficient to capture the degree of clustering in corporate defaults or the level of correlation in changes in firms' credit default swap (CDS) spreads. For example, Jarrow and Yu (2001) find that the inclusion of an unobserved (counterparty) risk factor is needed to generate the observed clustering in defaults. Das et al. (2007) reject the doubly stochastic assumption that defaults are independent conditional on the observed risk factors at the macro and the firm level. Their finding thus implies the possible existence of an unobserved or latent systematic risk factor that may affect all firms in the economy. Pu and Zhao (2012) find that more than 40% of the correlation in firms' credit risk changes – as captured by changes in credit default swap (CDS) spreads – may result from the unobserved risk factor, although the default probabilities reflected in CDS spreads are based on risk-neutral measures instead of real probability.

The intuition behind the unobserved systematic risk factor is that not all relevant risk factors are known and quantifiable for modeling and prediction purposes. For instance, the "institutional memory" problem, as discussed in Berger and Udell (2004), could lead to time-varying lending standards and procyclical lending behavior, which cannot be fully captured by the commonly observed macroeconomic factors or firm-level risk characteristics.

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* Corresponding author.
E-mail addresses: min.qi@occ.treas.gov (M. Qi), xiaofei.zhang@occ.treas.gov (X. Zhang), xinlei.zhao@occ.treas.gov (X. Zhao).

[1] These models range from the *reduced-form models*, including linear discriminant analysis (such as Altman's Z-score (1968)); logit models (such as Ohlson's O-score (1980)); duration models (such as Shumway (2001) and Hillegeist et al. (2004)); to the *structural models*, including the original Merton's model (1974) and the later modified versions with stochastic interest rates (such as Longstaff and Schwartz (1995)), endogenously determined default boundaries (such as Leland and Toft (1996)), mean-reverting leverage ratio policy (such as Collin-Dufresne and Goldstein (2001)), and strategic defaults (such as Anderson and Sundaresan (1996), Anderson et al. (1996) and Mella-Barral and Perraudin (1997)).

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In addition, unobserved systematic risk could come from differences in the assessment of hard and soft information on borrower quality and its implications for lending standards and default prediction, as shown by Grunert et al. (2005).[2] It is also challenging to directly measure the credit contagion found in Jorion and Zhang (2007, 2009), Lando and Nielsen (2010) and Giesecke and Kim (2011), and the unobserved systematic factor may be able to capture such credit contagion effect on default. Finally, during the financial crisis of 2007–2009, the government interventions, such as bank rescue programs, support programs for non-financial companies, and consumption stimulus programs, had impacted the economy and corporate default. However, it is difficult to convert such interventions into quantifiable factors. The unobserved systematic risk factor would be able to capture these systematic risk factors that are difficult to quantify.

There have been efforts to estimate the unobserved systematic risk factor and examine its impact on default model performance. These studies include Duffie et al. (2009), Azizpour et al. (2010) and Koopman et al. (2011). Among all the papers proposing methods to derive the unobserved factor, Duffie et al. (2009) is probably the most well-known and it immediately attracted extensive attention among academics and practitioners since the first version came out. These authors show that a model incorporating the unobserved systematic risk factor predicts portfolio losses more accurately than a model without such a factor. However, their study focuses on model development and thus does not thoroughly investigate the marginal contribution of the unobserved systematic risk factor in default prediction. In particular, their performance measure at the firm level is the ability to rank order firms' default risk rather than accurate prediction of the level of default risk (or predictive accuracy), and they mainly compare relative performance between models rather than measuring model performance against the realized default rates. This paper aims to enhance our understanding of the unobserved systematic risk factor from some additional aspects.

Our study contributes to the literature in the following ways. First, we find that, firm-level risk factors are the predominant drivers of default risk. This finding suggests that a default model or a model to derive the unobserved systematic risk factor has to incorporate firm-level factors. As such, the unobserved systematic risk factors backed out from Koopman et al. (2011) might have reflected observed firm-level risk characteristics that are omitted from their model.

Second, after controlling for firm-level risk characteristics, default risk seems to be more driven by the unobserved systematic risk factor than the observed systematic risk factors. Even though the observed systematic risk factors are statistically significant, incorporation of these factors can neither significantly improve the model's ability to rank ordering firms by default risk nor noticeably boost default predictive accuracy. The systematic risks in the default process are better captured by the unobserved systematic risk factor, and incorporating this latent factor drastically improves the in-sample default predicative accuracy. This finding suggests that it might be useful to consider the unobserved systematic risk factor when simulating portfolio credit losses to capture the incremental risk and comprehensive risk under the requirements of the new Basel market risk rules.

Third, although a model with unobserved systematic risk factor predicts default more accurately than a model without such a factor, the out-of-sample improvement is only marginal, and accurate prediction of default remains challenging. As a result, incorporating systematic risk factors, either observed or latent, may be of only limited value in default prediction or CDO tranche valuation. It is also worth noting that the role of the latent systematic factor is different in the latest financial crisis period. While we confirm the finding in the literature that including the unobserved systematic risk factor in default prediction models can help reduce under-estimation of default clustering in earlier crisis periods, this factor actually helps reduce the over-estimation in the most recent crisis period.

Lastly, we draw the distinction between two types of model performance measures, measures for rank ordering and measures for predictive accuracy, which has largely been overlooked in academic literature and industry practice. We show that a model with superior ability to rank order firms by default risk does not necessarily have superior predictive accuracy, i.e., to produce default rate forecasts that are close to the levels of the actual default rates. Therefore, future studies on default prediction models should evaluate model performance by both types of performance measures. We find that rank ordering is driven mainly by firm-level characteristics, while predictive accuracy is affected by firm-level characteristics, the latent systematic risk factor, and, to a lesser extent, the observed systematic risk factors.

The rest of the paper is organized as follows. In Section 2, we describe our sample. We investigate the relevance of the unobserved systematic risk factor and its out-of-sample performance in Section 3. The relevance of additional macroeconomic variables are investigated and discussed in Section 4. The final section summarizes our findings.

2. Sample description

A common challenge to default studies is the failure to identify all defaults in the sample data. In order to clearly identify defaults, we restrict our sample (i.e., both defaults and non-defaults) to those firms covered by the Moody's Corporate Default Risk Service (DRS) database. Moody's default definition includes missed interest payment, distressed exchange offers, reorganization, and bankruptcy. Many firms experienced several default events in sequence, for instance, missed interest payment followed by reorganization several months later. We set the default month for a firm to be the month of the first default event and the firm is considered to be in default starting from that default month. We restrict our sample to the period after 1978 because of the change in bankruptcy law.

We verify the identification information in Moody's with that in the Center for Research in Security Prices (CRSP). Moody's identifies a firm using firm name, cusip, and/or ticker. On multiple occasions, the cusip, ticker, and/or firm name do not match. In such cases, we exclude these firms from the data to get a clean sample of defaults and non-defaults. We then search for firm-level information in CRSP and Compustat, and, following common practice, we restrict our sample to nonfinancial firms, because the default risk drivers may be very different for financial firms.

We estimate the unobserved systematic risk factor under the framework of Duffie et al. (2009) using the same firm-level characteristics and observed systematic risk factors as those used in their study. The firm-level characteristics include trailing 1-month distance-to-default and trailing 1-year stock return. The distance-to-default is a measure of leverage adjusted by volatility; it is constructed on market equity data and Compustat leverage data,

[2] The assessment of "soft information" (such as management quality, industry perspectives, and market positions) tends to result in more favorable and less volatile risk ratings than the assessment of "hard information" (financial statements). "Soft information" and rating overrides cannot be fully captured by the commonly observed macroeconomic factors or firm-level risk characteristics, but are important channels through which lending standards might vary over time.