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The cross-section of consumer lending risk☆

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ABSTRACT

This paper tests the validity of a single-factor (market) model to price consumer lending risk. It classifies US counties into 25 portfolios based on unemployment level and the change in nominal income. The results, using serious delinquency on revolving credit as default risk, show that the intercepts are indistinguishable from zero in 22 portfolios, and the average default rate of a portfolio increases with its beta. The additional risk factors based on unemployment and income growth portfolios marginally improve the single-factor model. The results are robust to time-varying betas and personal bankruptcy as a measure of consumer lending risk.

1. Introduction

The modern portfolio theory helps consumer lenders manage credit risk. Using the time-series of borrowers' credit scores, Musto and Souleles (2006) compute the covariance risk of a borrower as the beta coefficient of the market model. They find that the credit availability decreases with a borrower's beta. Desai et al. (2014) find similar results using US counties data.[1] Both studies *assume* that the consumer credit risk follows a single-factor (market) model. This paper answers, how good is the assumption that the single-factor model is a valid model to price consumer lending risk. For that, it sorts US counties into 25 portfolios by income growth and unemployment level, and utilizes serious delinquency (default) on revolving credit and personal bankruptcy filings as a measure of consumer lending risk. The main finding is that the consumer lending risk largely follows a single-factor structure.

The application of the portfolio theory on consumer lending can be explained as follows. Suppose that, at the beginning of a period, a credit card company extends a credit of $1 to each consumer of a hypothetical economy. The economy has 25 groups of 100 consumers each, and for simplicity, it is assumed that the lender's expected return, r, is the same for each group.[2] At the end of the period, if all 100 consumers of the first group repay the loan, then the lender earns an actual return equal to the expected return. During the same period, if some consumers of the second group default then the lender earns $r-\Delta_2$, where Δ_2 takes into account the reduction in return due to defaults in the second group. On aggregate, assuming zero recovery, the lender receives $2,500 minus the

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[1] In the case of subprime mortgage lending, Cowan and Cowan (2004) show that lower quality loans, as measured by its borrowers' credit worthiness, have not only higher default rates but also higher default correlation.

[2] Cowan and Cowan (2004) form the groups based on borrower riskiness, and in Desai et al. (2014), they are based on geographical location.

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total number of defaulting borrowers in that period, and earns a return of $r-\Delta_a$, where Δ_a takes into account the reduction in return due to aggregate defaults. The lender has information on the loan performance of each group and that of the overall economy across periods. Using time-series returns data, the lender can compute the beta of each group using the market model. Unlike the credit score, the beta captures the sensitivity of an individual group return to the overall return.[3] The information content of beta helps the lender in identifying new customers, extending credit lines to existing customers, monitoring the loan performance, or pricing. The underlying assumption is that the return on a consumer loan follows a single-factor structure.

To academic researchers, the challenge is to obtain the time-series data on consumer lending returns since the lender privately holds them. Musto and Souleles (2006) address this issue by computing monthly default probabilities of a borrower from her credit score and use the change in default probability as a proxy of the return. Desai et al. (2014) use credit score, default rate, and personal bankruptcy rate of a US county to compute its three versions of beta. In both these studies, the authors compute betas of individual borrowers or individual counties, because their research question involves assessing the effect of the covariance risk on credit availability.

The research objective of this paper is to validate whether the single-factor (market) model is an appropriate model for computing beta. Therefore, the unit of analysis is the portfolio of counties instead of individual counties. It helps restrict the number of test assets at a manageable level, which in turn, allows us to use the tools from the empirical asset pricing literature. In addition, a portfolio of counties better explains the time-variation of the credit outcome, and it minimizes the influence of county-specific characteristics in driving the results.

The results show that the single-factor structure describes the average default. The intercepts of the market model are indistinguishable from zero in 22 of 25 portfolios. The magnitude of an intercept, on average, is 6 percent of a portfolio's default rate, suggesting an economically small value. The pattern of expected default rate is largely matched with the pattern of beta. In addition, the credit availability of a portfolio decreases with its beta, which indicates that the consumer lenders price the covariance risk. Further, the betas vary over-time. The intercept from the conditional single-factor model, however, is indistinguishable from zero in only five portfolios, suggesting that the conditional single-factor model is not as good as the unconditional single-factor model. The additional risk factors using portfolios of unemployment and income growth marginally improves the single-factor model.

The defaults on consumer loans and personal bankruptcy filings, in general, are correlated. A default on a loan is a sign of financial distress and filing for bankruptcy is the remedy. Several instances suggest otherwise. In a state with low wage garnishment and borrowers' private right of action against aggressive collection efforts, a defaulter finds bankruptcy filing unwarranted (Dawsey and Ausubel, 2004; Dawsey et al., 2013; Desai et al., 2014). Personal bankruptcy filing is expensive after the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005. An unemployed borrower may default on a loan, but finds bankruptcy filing unaffordable. In some cases, a borrower strategically files for bankruptcy without defaulting to benefit from the borrower-friendly bankruptcy code (White and Zhu, 2010). A borrower who is late on mortgage payments files bankruptcy to save her home. The discharge of unsecured credit and the bankruptcy process provide additional time and financial resources to remain current on mortgage payments (Berkowitz and Hynes, 1999; Desai, 2016b). Therefore, the information content of both default rate and bankruptcy rate is important to an unsecured lender.[4] The results based on bankruptcy filings provide robustness to those obtained using default rate as a measure of consumer lending risk. The single-factor beta explains the average bankruptcy risk. The additional risk factors based on unemployment and income growth portfolios marginally improve the single-factor model.

2. Default rate as a measure of consumer lending risk

2.1. Data

The unbalanced panel data are for 3108 US counties from the first quarter of 1992 to the fourth quarter of 2008. The default rate is the ratio of revolving credit borrowers who are late on their payments above 90 days to the total revolving borrowers, and it is expressed in percentages. The default data are from TrenData database. It tracks consumers' credit use and payment behavior at various levels of geographic aggregation using the credit reporting files of TransUnion LLC.[5] The unemployment rate is the percentage of the total number of people in the labor force who are looking for a job. The unemployment data are from the Bureau of Labor Statistics (BLS). The change in nominal income (income growth) is the ratio of the change in nominal per capita income in the current year to the nominal per capita income of the previous year, and it is expressed in percentage. The per capita income and population data are from the Bureau of Economic Analysis (BEA), and the US Census, respectively.[6]

[3] The credit score is a stand-alone measure of credit risk. It helps predict the probability of default in the next two years. A borrower's current level of debt, past credit performance, and length of credit history are the main inputs for computing her credit score.

[4] Approximately 14 percent of consumers have been under third party debt collection in recent years (Federal Reserve Bank of New York, 2015), and the industry collected over $55 billion in 2013 (Ernst and Young, 2013). As per FICO (2016), each year the financial services industry loses billions of dollars due to bankruptcy filings. Therefore, the lenders rely on credit and bankruptcy risk scores in their lending decisions (Yuille 2006).

[5] TrenData is based on a time-series of large random samples of US consumer credit histories. Each quarterly sample starting from 1992 contains approximately 30 million anonymous credit reports. From this database, variables related to a borrower's debt and payment behavior are built and aggregated at the county, state, and national levels. See Barron et al. (2000) for further discussion on TrenData.

[6] In the case of Virginia, there are 24 instances when the local area definitions of the BEA and Census/BLS/TrenData differ. This is because the BEA does not separately report per capita income of a city engulfed by a county. Using the approach of Moody's analytics, the population, unemployment, and default data are aggregated to conform to the BEA's local area definitions, see https://www.economy.com/support/blog/buffet.aspx?did=869A03D1-5D74-4376-A606-00A8C64DDB0B. (Last accessed on 6/22/2016).