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County-level bankruptcy beta and its impact on the supply of revolving credit

Abstract

A county's bankruptcy rate conveys information on the investment returns on lending to consumers in a county. The covariance of a county's bankruptcy rate with those of other counties reflects the county's contribution to portfolio risk. Applying this insight, the authors compute county-level "bankruptcy" betas, market model coefficients on national bankruptcy rates. The paper finds considerable heterogeneity in betas across counties, which is in part explained by local economic conditions and demographics. Although lenders appear to consider the information conveyed by bankruptcy betas in offering revolving credit, their estimated effect on credit supply is quite small. The small estimated supply effect suggests the possibility that consideration of covariance risk can better assess portfolio risks in account acquisition and management. Aggregate county-level data are readily available to implement this portfolio approach.

Keywords: consumer credit, risk, bankruptcy.
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Introduction

In the United States, the personal bankruptcy rate has grown rapidly over the last two decades (Figure 1, see the Appendix). The Bankruptcy Abuse Prevention and Consumer Protection Act produced a surge in bankruptcy filings in advance of its effective date in October 2005, followed by sharp decline in filings in 2006. Bankruptcy filings quickly resumed their rapid rate of growth in subsequent years. Although the trend since 2010 has been negative as creditors tightened underwriting standards thereby limiting credit available to higher risk borrowers (Han, Keys and Li, 2012), bankruptcy will remain an important concern in assessing risks in consumer lending, especially for unsecured lenders.

Lenders clearly have reasons to devote considerable effort to manage risk and clearly do so. They use statistical models to estimate the probability of bankruptcy or serious delinquency for screening applicants, determining loan prices, and allocating collection resources[1]. In this paper, we argue that information in county-level bankruptcy rates may help creditors further reduce the overall portfolio risk. The personal bankruptcy rate of a county conveys information on the investment returns (credit losses) to a consumer lender. The level of bankruptcy rate of a county for a given period captures information on the incidence of the same-period credit losses. The change in bankruptcy rate for that period allows lenders to revise their expectations about the future-period credit losses. Most large lenders hold a portfolio of loans spread across various geographic areas but appear not to give much consideration to covariances across areas (Nadaud and Sherlund, 2001). Portfolio theory suggests that covariances of a county's bankruptcy rate with other counties' bankruptcy rates should be an important consideration for reducing the overall portfolio risk.

We apply these ideas within a market model framework to compute a "bankruptcy" beta for each county. We find considerable heterogeneity in betas across counties. The condition of a county's labor market and its demographic characteristics influence its bankruptcy beta. This paper then examines the impact of a county's bankruptcy beta on its supply of revolving credit, measured by the line of credit associated with a credit card account. These lines are unsecured, and amounts borrowed against these lines are most at risk of discharge in bankruptcy. Our findings indicate that lenders are currently capturing some of the information in a county's bankruptcy beta while extending the revolving credit. However, the impact of beta on credit supply is significantly lower than the impact of credit risk score on credit supply, suggesting the possibility of further improvements.

1. Contribution to the literature

Musto and Souleles (2006) first applied the concepts of portfolio theory to consumer credit. Using proprietary data on credit risk scores from a credit reporting agency, they computed individual consumers' default betas. Musto and Souleles' analysis suggested to them that lenders could enhance their credit risk models by incorporating information on default betas. The difficulty with Musto and Souleles' approach is that it relies on historical credit files data. Historical data are

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[1] The Fair Isaac Company (FICO) credit risk scores rank consumers based on predicted probability of bankruptcy, serious delinquency, or other major derogatory events (e.g. charge-off, collection or garnishment) over the next two years. The prediction is derived from a statistical analysis of information in consumers' credit bureau files. See Bailey (2004) for a discussion of the credit evaluation and collection practices of lenders.

not generally available to lenders, however. The Fair Credit Reporting Act of 1970 allows lenders to purchase from a credit reporting agency only the current records in individuals' credit files, not the data from their historical credit files. This restriction largely precludes the lender from computing consumers' default betas[1].

Our approach using geographic variations is more intuitive and practical to implement than that of Musto and Souleles. Different geographic areas have various mixes of industries, labor force dynamics, and levels of diversification. Local conditions make some areas more vulnerable to macroeconomic developments than others. County-level bankruptcy betas directly measure the degree of vulnerability. This concept is easily understood, and county-level data for calculating bankruptcy betas are available from the Administrative Office of the U.S. Courts and other government agencies. Bankruptcy betas may be useful for managing risk on an existing portfolio of consumer loans and acquiring new accounts through solicitations or acquisitions. Consideration of local bankruptcy betas is also attractive because data on local economic conditions are not collected very frequently and are not published on a timely basis. For example, county-level income data are available with a lag of around two years. Furthermore, the local area data on bankruptcy rates are closer to what investors in asset-backed securities work with if they want to assess portfolio risk on their own[2].

2. Bankruptcy rate as a proxy for returns

Using a simple conceptual framework, we demonstrate that the bankruptcy rate of a county for a given period, say a month, can be a valuable proxy for the returns experienced by the lender. We ignore any interest income generated from a consumer loan since we are unable to observe it. Consider a county i where historically the residents never filed for personal bankruptcy before January 2011. Suppose, each borrower of county i is allocated a consumer loan of \$1, and there are 1,000 borrowers. Because the expected bankruptcy rate is 0, at the beginning of January 2011, investors seeking to purchase these loans are willing to pay \$1,000. Similarly, the lenders who issued these loans expect to receive \$1,000 when the loans mature. Now, suppose the *actual* bankruptcy rate in county i for January 2011 is six (6 out of 1,000 consumers filed for personal bankruptcy). Assuming no partial recovery for loans in bankruptcy court, lenders incur a loss of \$6 in January 2011.

Suppose bankruptcy rates for subsequent periods (February, March, etc.) remain at the same level as in January. Although the levels of bankruptcy rates for January and February are both equal to 6, they convey different information regarding changes in expectations of future-period credit losses. For example, at the beginning of February, the lenders' revised expectations are to receive \$994 from 1,000 loans of \$1. Similarly, investors are willing to pay only \$994 for \$1,000 in consumer loans. The change in bankruptcy rate from 0 to 6 in January revised expectations for future period credit losses. In the case of a bankruptcy rate of 6 for February, it conveys information only on the same-period incidence of credit losses. Since the *change* in bankruptcy rate in February is zero, it does not convey information on the changes in expectations for future period credit losses. In the following paragraphs, we explain this intuition using a simple mathematical framework.

Suppose the expected rates of bankruptcy for a given county i are X, Y, and Z per 1,000 borrowers for months 1, 2, and 3, respectively. For simplicity assume that each borrower has a \$1 loan. Suppose an investor buys the \$1,000 portfolio at time $t = 0$, the beginning of the first month. The expected price of this portfolio at $t = 0$ is $\hat{P}_0 = (1000 - X - Y - Z)$. Similarly, $\hat{P}_1 = (1000 - Y - Z)$ and $\hat{P}_2 = (1000 - Z)$. The expected rate of return for this investor for the first month ($\hat{r}_1$) is the ratio of differences in prices of the portfolio at $t = 1$ and $t = 0$ to the price of the portfolio at $t = 0$. Mathematically, $\hat{r}_1 = \frac{(\hat{P}_1 - \hat{P}_0)}{\hat{P}_0}$. After substituting values of $\hat{P}_1$ and $\hat{P}_0$ and some minor algebra, $\hat{r}_1 = \frac{(Y-X)-Y}{(Y+Z)-(1000-X)}$. Similarly, $\hat{r}_2 = \frac{(Z-Y)-Z}{Z-(1000-Y)}$, and $\hat{r}_3 = \frac{Z}{(1000-Y)}$.

The values of $\hat{r}_1$ and $\hat{r}_1$ suggest the expected rate of return for a given period depends on the change in bankruptcy rate for the next period and level of the bankruptcy rate for the same period.

3. Bankruptcy betas

3.1. County-level average bankruptcy rate. Our county-level bankruptcy filing data are from Lunquist Consulting, a firm specializing in providing bankruptcy statistics and analytics. We measure the

[1] One way to offset this limitation, as suggested by Musto and Souleles, is to estimate default betas based on individuals' demographic characteristics.Why one individual's default beta should differ from that of another may be hard to explain, which risks alienating potential customers and attracting regulatory scrutiny. Moreover, the Equal Credit Opportunity Act (ECOA) of 1974 prohibits consideration of many personal characteristics in lending decisions.

[2] In an analysis of subprime mortgage securitizations, Nadauld and Sherlund (2009) found that pools of mortgages concentrated in geographic areas with higher housing price appreciation received AAA ratings on a larger percentage of the principal.

bankruptcy rate as the ratio of the number of bankruptcy filings (Chapters 7 and 13) to the population per 1,000 persons. The data cover the 96-month period from January 1999 to December 2006. The average bankruptcy rate during the sample period varied widely across counties in the U.S. but also widely within some states (Figure 2, see the Appendix).

3.2. Computation of bankruptcy betas. We use a market model framework and monthly bankruptcy data from 1999-2006 to compute bankruptcy beta − our measure of covariance risk − for each county in two ways[1]. First, we compute betas based on levels of bankruptcy rates as given below:

$$BKR_{i,t} = \alpha_i + Beta_i \times NationalBKR_t + \varepsilon_{i,t}, \qquad (1)$$

where $BKR_{i,t}$ and $NationalBKR_t$ are bankruptcy rates for county i and the U.S. in month t, respectively[2]. In the second approach, we compute betas based on the first-difference of bankruptcy rates of a county by the following regression:

$$BKR_{i,t} - BKR_{i,t-1} = \alpha_i + Beta_i \times \times (NationalBKR_t - NationalBKR_{t-1}) + \varepsilon_{i,t}. \qquad (2)$$

The regression coefficient $Beta_i$ in equation (1) is the ratio of change in the bankruptcy rate of county i to the change in the aggregate bankruptcy rate. The regression coefficient $Beta_i$ in equation (2) is the ratio of change in first-difference of the bankruptcy rate of county i to the change in the first-difference of aggregate bankruptcy rate. A beta coefficient in equation (1) of unity indicates the magnitude of change in the county's bankruptcy rate is the same as the change in the aggregate bankruptcy rate. A beta coefficient larger (smaller) than one indicates the county's bankruptcy rate changes in a higher (lower) proportion than the aggregate rate. A county's bankruptcy filings could be uncorrelated (zero beta) or inversely related (negative beta), but such instances should be relatively infrequent as economic activities are generally interrelated.

When estimating bankruptcy betas, we compute Dublin-Watson statistics and adjust for autocorrelation when warranted[3]. We make adjustments for 1,233 of the 3,140 (39%) counties when computing betas using equation (1). Models estimating bankruptcy betas generally explain a large percentage of the variation in county bankruptcy rates. Half of the regressions explain 65% or more of the variation in county bankruptcy rates, and three-quarters explain 40% or more. When estimating betas based on equation (2), we adjust for autocorrelation for only one county. Here also, the models estimating betas explain a large percentage of variation in county bankruptcy rates. Half of the regressions explain 60% or more of the variation in county bankruptcy rates, and three-quarters explain 32% or greater.

3.3. Distribution of bankruptcy betas. The range of county bankruptcy betas is quite wide. Estimated over the 1999-2006 period using equation (1), the minimum value of beta is -0.09, and the maximum value is 4.15 (Panel A of Table 1). A considerable share of betas is concentrated around the average value of 0.92[4]. A quarter of betas are between 0.84 (the 50^{th} percentile) and 1.17 (the 75^{th} percentile), a result that reflects the integration of geographic areas in the U.S. economy. There are practically no negative-beta counties and a very small number of low-beta counties. Nevertheless, a large percentage of counties have betas that are considerably less than 1. Forty percent of counties have betas between 0.39 and 0.84. Borrowers in these counties contribute relatively little diversification benefits to a well-diversified loan portfolio. In contrast, a few counties have high levels of covariance risk. Ten percent of counties have betas of 1.55 or greater, and one percent of them have betas more than 2.40.

Table 1. Distribution of county-level bankruptcy betas

	Panel A	Panel B		
	Beta based on levels of county and national bankruptcy rates	Beta based on the changes in county bankruptcy and national bankruptcy rates		
	Using data of 1999-2006	Using data of 1999-2005	Using data of 1999-2006	Using data of 1999-2005
Mean	0.922	0.923	0.9000	0.8999
Minimum	-0.091	-0.172	-1.099	-1.100
Maximum	4.147	4.178	4.270	4.273
Std. dev.	0.483	0.512	0.514	0.514

[1] Monthly data are typically used in practice and academic research to compute equity betas. In the case of the academic literature, see Blume (1970) and Sharpe and Cooper (1972). In practice Merrill Lynch, Zacks, and Yahoo Finance use monthly observations for the last five years to compute betas (Reilly and Brown, 2006; Brigham and Ehrhardt, 2008).

[2] For each month, we compute the $NationalBKR_t$ as the ratio of total number of bankruptcy filings in the U.S. to the entire U.S. population per 1,000 persons. Therefore, $NationalBKR_t$ is equivalent to the value-weighted index, where weights are the population of each county over the U.S. population.

[3] In the case of equity beta computation, Ibbotson, Kaplan and Peterson (1997) note that market returns data are highly autocorrelated and argue for adjusting beta for autocorrelation.

[4] We also estimated betas using an equally weighted average of the bankruptcy rate of each county for that month. The mean and median values of betas from these regressions are 1.005 and 0.918, respectively.

Table 1 (cont.). Distribution of county-level bankruptcy betas

	Panel A	Panel B		
	Beta based on levels of county and national bankruptcy rates	Beta based on the changes in county bankruptcy and national bankruptcy rates		
	Using data of 1999-2006	Using data of 1999-2005	Using data of 1999-2006	Using data of 1999-2005
Percentile				
1st	0.073	0.006	-0.011	-0.011
5th	0.277	0.238	0.213	0.213
10th	0.391	0.356	0.341	0.340
25th	0.589	0.568	0.551	0.551
50th	0.845	0.846	0.817	0.817
75th	1.170	1.196	1.176	1.176
90th	1.554	1.601	1.570	1.570
99th	2.397	2.465	2.449	2.447
N	3140	3140	3140	3140

Note: This table reports the summary statistics of the county-level bankruptcy beta. Panel A (Panel B) betas are based on OLS analysis on the levels (first-difference) of monthly county bankruptcy rates on national bankruptcy rates. Bankruptcy rate is the ratio of number of bankruptcy to population per 1000 persons. We test for the autocorrelation using the Dublin-Watson statistic, and when required, we estimate the beta with AR(1) adjustment. For the betas reported in Panel A, we make such an adjustment for 1233 and 1041 counties for the sample period of 1999-2006 and 1999-2005, respectively. For Panel B betas, only one county requires such an adjustment. *N* stands for the number of counties.

In Panel B of Table 1, we report the distribution of bankruptcy betas where the betas are computed using the first-difference in monthly bankruptcy rates (equation (2)). The distribution is similar to Panel A. We also report the distribution of betas estimated for the period of 1999-2005. Later, these betas are used for analyses on the supply of revolving credit for year 2006 as discussed in subsection 5.2.

Like bankruptcy rates, bankruptcy betas varied widely across counties during 1999-2006 (Figures 2 and 3, see the Appendix). In some states (South Carolina and Indiana, for example), county bankruptcy betas differ little. In other states, Pennsylvania and Michigan, variation in betas across counties is notable. Bankruptcy betas and bankruptcy rates are positively correlated, but some states have quite a few counties with high bankruptcy rates and low betas (Tennessee and Georgia, for example) or low bankruptcy rates and high betas (Colorado and Nevada). The distribution of betas based on first differences in monthly bankruptcy rates (Figure 4, see the Appendix) is similar to the one shown in Figure 3. The coefficient of correlation between betas computed using the levels of and the first-differences in bankruptcy rates is 0.98.

4. Description of additional variables

Table 2 provides descriptive statistics, definitions, data sources, and the time period for our variables. Our measure for the supply of revolving credit for a county is the ratio of total amount of revolving credit limits to the total number of revolving accounts for that county. The explanatory variables fall into three broad categories: credit risk, local economic conditions, and demographic characteristics.

Table 2. Variable description and descriptive statistics

Variable name	Variable definition (and source)	Mean	Std. dev	*N*	Based on
Bankruptcy filing					
BKR	Number of bankruptcy filings per 1000 population (Lundquist Consulting and US Census Bureau)	4.605	2.244	3141	Avg. of 1999-06
Credit supply					
Credit Supply	Ratio of revolving credit line to revolving account in $1000s (TrenData)	6.868	1.374	3136	Year 2006
Δ*Credit Supply*	Change in *Credit Supply* compared to previous year	0.297	0.354	3136	Year 2006
Avg_Credit Supply	Average credit supply in $1000s (TrenData)	4.924	0.730	3137	Avg. of Q1 '92- Q4'06
Credit risk					
Score	TransRisk credit risk score, which is the Trans Union LLC's generic credit score (TrenData)	660.49	35.48	3141	Avg. of Q4 '98- Q3'06
Local economic conditions					
Income per Capita	Ratio of income to total population in $1000s (Bureau of Economic Analysis and Census Bureau)	22.274	5.227	3140	Year 1992-06
Annual Income Growth	Geometric average of yearly growth rate of income per capita (Bureau of Economic Analysis and Census Bureau)	0.036	0.019	3140	Year 1992-06

Table 2 (cont.). Variable description and descriptive statistics

Variable name	Variable definition (and source)	Mean	Std. dev	*N*	Based on
Employment Concentration	Sum of squared industry employment ratios (Bureau of Economic Analysis and Census Bureau)	0.099	0.029	3139	Year 2001-06
Unemployment Rate	Ratio of people seeking a job to the total number of people in the labor force (Bureau of Labor Statistics)	0.057	0.022	3140	Avg. of 1992-06
Uninsured	Percentage of population not covered by health insurance (Census Bureau)	0.148	0.050	3138	Year 2000
Demographic characteristics					
Age less than 14	Percentage of population $\leq$ 14 years of age (Census Bureau)	0.208	0.028	3141	Avg. of 1992-06
Age 15 to 24	Percentage of population 15 to 24 years of age (Census Bureau)	0.137	0.032	3141	Avg. of 1992-06
Age 25 to 44	Percentage of population 25 to 44 years of age (Census Bureau)	0.276	0.032	3141	Avg. of 1992-06
Age 45 to 64	Percentage of population 45 to 64 years of age (Census Bureau)	0.230	0.024	3141	Avg. of 1992-06
Singles	Percentage of adults who are single i.e. never married (Census Bureau)	0.178	0.045	3139	Year 2000
Divorced	Percentage of adults who are divorced (Census Bureau)	0.075	0.016	3138	Year 2000
Population Density	Population per square miles in thousands (Census Bureau)	0.241	1.662	3136	Avg. of 1992-06

Note: *N* stands for number of counties.

Score represents a measure of the overall credit risk of a county. It is the average credit risk score of all borrowers in that county. Credit risk score is an ordinal ranking of borrowers' probability of default, with higher scores indicating lower probability of default and higher level of credit supply.

We use five variables to describe a county's economic conditions: *Income per Capita*, *Annual Income Growth*, *Employment Concentration*, *Unemployment Rate*, and *Uninsured*. *Income per Capita* of a county is the ratio of its income to population in $1,000s. *Annual Income Growth* is the annual growth rate of per capita income. *Unemployment Rate* is the ratio of people seeking jobs to the total number of people in the labor force. *Uninsured* is the percentage of the population that does not have health insurance. Higher unemployment, larger percentages of uninsured individuals and lower income growth suggest greater default risk with reduced credit availability.

Employment Concentration is a Herfindahl index measuring the degree to which a county's labor market is concentrated in industry categories. We use the county-level number of people employed across industries for the years 2001-06 from the U.S. Bureau of Economic Analysis. The Herfindahl index is computed as the sum of the squares of the proportion of the number of employees in two-digit North American Industry Classification System categories[1]. A value of *Employment Concentration* close to zero (one) suggests a lower (higher) level of employment concentration. Higher employment concentration could reasonably be hypothesized to be positively related to beta. Less diversified counties may be more susceptible to economic downturns. However, some evidence suggests that concentration may be less, not more risky[2].

Finally, demographic variables include the age distribution of the population, population density, and the distribution of the population by marital status. *Population Density* has been used as a proxy for stigma associated with bankruptcy. More densely populated areas are hypothesized to provide greater anonymity, which reduces the likely loss in reputation from filing for a bankruptcy. The age distribution reflects life-cycle characteristics, with greater percentages of the population in early life-cycle stages (ages 25-44) and higher percentages of children (age less than 15) using more credit than at later life-cycle stages. Single (never married) individuals would be less likely to form households than married (or living as married individuals). Divorce and financial stress are often found in the same families.

5. Empirical methodology

5.1. Heterogeneity in bankruptcy betas. For assessing the effects of local economic conditions and demographic characteristics of a county on its bankruptcy beta, we run the following regression:

$$Beta_i = \psi_0 + \psi_1 X_i + \psi_2 Z_i + \varepsilon_i, \quad (3)$$

[1] For confidentiality reasons, the U.S. Census Bureau does not publish employment in selected industries in a few counties in some years. We imputed values of 95,378 missing observations (out of a total of 545,490) based on population data. For improved accuracy, the values are imputed five times and an average value is employed.

[2] Melicher and Rush (1973) find that conglomerates tend to have higher equity betas than more specialized firms. Bennett and Sias (2006) and Hou and Robinson (2006) show that firms operating in concentrated industries tend to have lower levels of return and firm-specific risk.

where $Beta_i$ is the covariance risk of county i as estimated by equation (1) for the period of 1999-06. X and Z are vectors of independent variables measuring the local economic conditions and demographic characteristics of a county, respectively. We use the average values of these variables for the period as shown in the last column of Table 2. We also include the credit risk score of a county in some of the regressions, primarily to assess whether the credit score of a county conveys additional information in explaining bankruptcy betas.

5.2. Bankruptcy beta and supply of revolving credit. *5.2.1. Using the level of credit supply.* To assess the impact of bankruptcy beta on credit supply, we estimate the following regression:

$$Credit\ Supply_{i,06} = \gamma_0 + \gamma_1 Score_{i,05} + \\ + \gamma_2 Beta_{i,99-05} + \gamma_3 X_{i,05} + \gamma_4 Z_{i,05} + \varepsilon_i, \quad (4)$$

where the dependent variable $Credit\ Supply_{i,06}$ is the total revolving credit line per number of revolving accounts (in \$1,000s) in 2006 for county i. To avoid problems arising from endogeneity of credit supply and covariance risk, we use lagged values for the explanatory variables. We estimate bankruptcy beta using 1999-2005 data. For *Uninsured*, *Singles*, and *Divorced*, we use 2000 values, the latest available pre-2006 data. For all other variables, we use 2005 values[1].

Our analysis focuses mainly on coefficient γ_2. A negative value suggests that after controlling for credit risk, local economic conditions, and demographic characteristics, a county with a higher beta is likely to receive a lower level of revolving credit. In addition, we look at the effect that a given change in beta would have on the supply of credit and compare that estimated effect with the effect of changes in credit scores.

5.2.2. Using the change in credit supply. We estimate the following regression:

$$\Delta(Credit\ \ Supply)_{i,06} = \gamma_0 + \\ + \gamma_1 Credit\ \ Supply_{i,05} + \gamma_2 Beta_{i,99-05} + \\ + \gamma_3 \Delta(Score)_{i,05} + \gamma_4 Beta_{i,99-05} \times \\ \times \Delta(Score)_{i,05} + \gamma_5 X_{i,05} + \gamma_6 Z_{i,05} + \varepsilon_i, \quad (5)$$

where the dependent variable $\Delta(Credit\ Supply)_{i,06}$ is the change in revolving credit supply for county i in 2006. Our focus is mainly on coefficient γ_4. A negative sign for γ_4 suggests that lenders consider county's covariance risk while increasing or decreasing the supply of revolving credit with the increase or decrease in the change in credit score for that county[2].

The significance of the coefficients for beta (γ_2), change in credit score (γ_3), and their interaction term (γ_4) suggests two things. First, a county's differential change in credit supply relative to its differential beta depends on its level of beta and on its change in credit score. Second, a county's differential change in credit supply relative to its differential change in its credit score depends not only on the change in credit score but also on its beta.

6. Results

6.1. Heterogeneity in bankruptcy betas. In Table 3, we report the results based on equation (3). In Model 1, we include variables that proxy for local economic conditions to explain cross-sectional variation in bankruptcy beta. The results indicate the negative influences of county-level income per capita, employment concentration, and percentage of uninsured population on covariance risk of that county. The coefficient of -0.009 on *Income per capita* suggests that an increase in a county's income per capita by one standard deviation (\$5,227) decreases its bankruptcy beta by 0.047, ceteris paribus. This change is statistically significant at the 1% level. Considering the average value of bankruptcy beta is 0.92, the effect of income per capita on beta is also economically significant. The negative relationship between employment concentration and beta is consistent with evidence in Melicher and Rush (1973) and Hou and Robinson (2006) suggesting that concentration in business activities is inversely related to risk. The negative coefficient for the percentage of the population without health insurance (*Uninsured*) may reflect employment characteristics of the county − perhaps, for example, fewer jobs in unionized manufacturing companies, which are sensitive to national business conditions. A more flexible labor market may be resilient to adverse business conditions. Moreover, not all studies of bankruptcy find a significant relationship between insurance coverage and bankruptcy[3].

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[1] Lusardi (2006), commenting on Musto and Souleles (2006), suggested two-stage least squares as an alternative approach to address endogeneity of credit supply. We also estimated a model for credit supply using two-stage least squares. A Hausman test rejects the hypothesis that the supply and beta are exogenous. Results of estimation are similar to those reported for equation (4) in Table 4.

[2] If we take a partial derivative of equation (5) with respect to $\Delta(Score)$, we get $\frac{\partial \Delta Credit\ Supply_{i,06}}{\partial \Delta Score_{i,05}} = \gamma_3 + \gamma_4 \times Beta_i$. Consider two counties j and k with covariance risk of $Beta_j$ and $Beta_k$, respectively, and $Beta_j > Beta_k$. Assuming that due to some external shock in 2005, both counties experience the same level of net increase in the credit score, say by one unit, $\partial \Delta Score_{j,05} = \partial \Delta Score_{k,05} = 1$. We can show that $\partial \Delta Credit\ Supply_{j,06} - \partial \Delta Credit\ Supply_{k,06} < 0$, if $\gamma_4 < 0$. This means the net increase in the supply of revolving credit is at a lower level for county j than that for the county k, even though both the counties have the same level of net increase in credit score, because $Beta_j > Beta_k$. In the results section, we illustrate this with a numerical example.

[3] See Himmelstein et al. (2005) and Dranove and Millenson (2006).

Table 3. Heterogeneity in county-level bankruptcy betas

	Model 1	Model 2	Model 3	Model 4	Model 5
Income per Capita	-0.009*** [-5.31]		-0.008*** [-4.07]		-0.005** [-2.44]
Annual Income Growth	0.373 [1.22]		-0.021 [-0.03]		-0.174 [-0.24]
Employment Concentration	-2.013*** [-5.83]		-1.063*** [-3.59]		-0.936*** [-3.15]
Unemployment Rate	2.100*** [4.87]		0.710* [1.67]		0.315 [0.74]
Uninsured	-2.524*** [-13.31]		-3.210*** [-16.58]		-3.685*** [-16.04]
Age less than 14		-0.114 [-0.27]	2.411*** [5.51]		2.163*** [4.96]
Age 15 to 24		0.124 [0.24]	0.492 [0.97]		0.353 [0.69]
Age 25 to 44		0.307 [0.99]	-1.003*** [-3.18]		-1.619*** [-4.53]
Age 45 to 64		-3.151*** [-4.62]	-2.791*** [-4.43]		-2.579*** [-4.11]
Singles		-1.365*** [-4.12]	-1.088*** [-3.16]		-1.104*** [-3.25]
Divorced		1.121*** [18.12]	12.369*** [19.84]		11.777*** [18.93]
Population Density		0.012* [1.93]	0.022*** [3.37]		0.022*** [3.23]
Score				-0.001*** [-3.33]	-0.002*** [-4.43]
Intercept	1.556*** [22.14]	0.973*** [3.55]	1.251*** [4.85]	1.464*** [8.87]	2.592*** [6.45]
N	3136	3134	3132	3140	3132
Adjusted R^2	0.07	0.13	0.20	0.00	0.21

Note: This table reports the results of the OLS analysis on the county-level bankruptcy beta, which is computed using the monthly data of bankruptcy rates for 1999 to 2006. Detailed description of the explanatory variables is given in Table 2. The *t* values are in brackets below the coefficients, based on the robust standard errors. Symbols ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

In Model 2 of Table 3, we use variables reflecting the demographic characteristics of counties. We find that county bankruptcy betas are lower for counties with a larger population percentage for age group 45 to 64 (the age group where income is generally growing) than counties with larger percentages of individuals 65 or older. Betas are lower for higher percentages of single individuals and greater for higher percentages of divorced residents. There is also a positive relationship between population density and beta.

We incorporate both local economic conditions and demographic characteristics variables in Model 3 to explain the covariance risk of a county. An adjusted R^2 of 0.20 indicates the empirical specification accounts for 20% of the variability in bankruptcy betas in our dataset. In Musto and Souleles (2006), a specification involving economic conditions and demographic characteristics of individuals for explaining heterogeneity in default betas, the R^2 was close to zero even though the sample size was almost one million observations. Therefore, county-level bankruptcy data offers some advantages.

In Model 4, a county's beta is inversely related to its credit risk as measured by its *Score*. An increase in credit score of a county by one standard deviation decreases its beta by 0.035. Although this relationship is statistically significant, the impact is small economically. Both the coefficient estimate and the model's R^2 are negligible. As the credit risk score is a prediction of the probability of bankruptcy (or the bankruptcy rate in a geographic area), this result suggests that beta and the bankruptcy rate do not provide the same information about the credit risk in a county[1]. Finally, in Model 5, we include all independent variables – related to economic conditions, demographic characteristics, and credit risk – to explore the heterogeneity in bankruptcy betas. Including *Score* increases the R^2 marginally from .20 to .21. This result suggests that lenders can obtain information on county-level bankruptcy beta from the county's economic and demographic characteristics without relying heavily on credit bureaus files.

[1] Although not detailed here, in a separate analysis we found the impact of *Score* on average bankruptcy rate was statistically significant and economically important with an adjusted R^2 of 0.15.

We also conducted an analysis similar to the one reported in Table 3 using values of bankruptcy betas based on the first-difference in the bankruptcy rates obtained from equation (2). Our results remain similar to those reported in Table 3[1]. The results indicate that counties' economic and demographic characteristics largely explain the heterogeneity in bankruptcy betas. Credit risk scores, which are highly predictive of county-level bankruptcy rates, do not help explain much variation in the betas. Risk management practices based on county's covariance risk may help reduce the overall portfolio risk.

6.2. Bankruptcy beta and credit supply. *6.2.1. Using the level of credit supply.* Table 4 reports the results of OLS analysis based on equation (4). As reported in Model 1, a county's bankruptcy beta is inversely related to its supply of revolving credit. The negative sign on beta is consistent with expectations. Counties with lower betas have higher revolving credit lines. A one standard deviation increase in bankruptcy beta decreases the revolving credit line per revolving account by \$86(≈ .512 × .168 × \$1,000), ceteris paribus. This change is statistically significant at the 1% level but quite small relative to the average credit limit (\$6,868 from Table 2). The R^2 value close to zero also supports the conclusion that beta explains almost no variation in credit supply.

In Model 2, we include variables for local economic conditions with bankruptcy beta. The coefficient of .121 for *Income per Capita* indicates that an increase of *Income per Capita* by \$6,883 in 2005 would increase the average revolving credit line by \$833 for 2006[2]. This change is not only statistically significant but also economically important. We find that employment concentration and percentage of population uninsured have inverse relationships with the supply of revolving credit.

Table 4. Bankruptcy beta and the level of credit supply for year 2006 (OLS)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Beta	-0.168*** [-3.85]	-0.240*** [-7.63]	-0.208*** [-4.73]	-0.119*** [-3.30]	-0.224*** [-7.12]	-0.267*** [-7.84]	-0.314*** [-10.12]
Income per Capita (2005)		0.121*** [14.74]			0.092*** [12.93]	0.116*** [12.59]	0.083*** [13.61]
Annual Income Growth (2005)		0.555 [1.03]			1.089** [2.39]	0.173 [0.34]	1.304*** [3.00]
Employment Concentration (2005)		-2.499*** [-3.39]			-3.088*** [-4.39]	-2.286*** [-3.13]	-2.359*** [-3.66]
Unemployment Rate (2005)		-1.233 [-0.89]			3.424*** [2.87]	-4.179** [-2.40]	
Uninsured		-3.565*** [-6.58]			4.522*** [9.26]	-1.817*** [-3.06]	
Age less than 14 (2005)			-1.579 [-1.31]		2.066** [2.09]	-2.993*** [-2.73]	3.610*** [3.83]
Age 15 to 24 (2005)			-0.691 [-0.37]		0.760 [0.58]	0.119 [0.08]	0.178 [0.14]
Age 25 to 44 (2005)			11.711*** [11.01]		11.553*** [14.89]	5.111*** [6.34]	9.184*** [12.85]
Age 45 to 64 (2005)			22.542*** [12.21]		7.239*** [5.87]	8.069*** [6.01]	7.383*** [5.98]
Singles			8.344*** [7.84]		4.428*** [5.53]	3.505*** [3.37]	4.983*** [6.72]
Divorced			-3.688** [-1.98]		11.588*** [9.06]	5.580*** [3.92]	13.065*** [10.10]
Population Density (2005)			0.032 [1.09]		-0.073*** [-3.30]	-0.073*** [-2.85]	-0.058*** [-2.75]
Score (2005)				0.020*** [32.73]	0.021*** [24.92]		0.017*** [21.02]
Intercept	7.023*** [126.96]	4.576*** [12.89]	-2.580*** [-2.90]	-6.050*** [-16.00]	-16.950*** [-18.32]	0.786 [1.12]	-13.147*** [-15.28]
N	3136	3132	3133	3136	3131	3131	3132
Adjusted R^2	0.00	0.49	0.21	0.28	0.65	0.54	0.64

Note: The dependent variable is the revolving credit line per revolving account (\$1,000s) and it is for year 2006. Beta is calculated based on the level of monthly bankruptcy rates from 1999 to 2005. Most of the independent variables are for year 2005, except *Uninsured*, *Singles*, and *Divorced* which are for year 2000. The *t* values are in square brackets below the coefficients using the robust standard errors. Detailed description of the explanatory variables is given in Table 2. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. *N* stands for number of counties.

[1] This additional table is available from the authors upon request.
[2] For 2005, the average and standard deviation of income per capita were \$27,455 and \$6,883, respectively, for 3,138 counties.

For Model 3, we only include variables measuring demographic characteristics with bankruptcy beta to explore the supply of revolving credit. Middle age groups (25-44 and 45-64) and singles have a positive influence on credit supply. The significance of these variables likely reflects the spending and payment behavior of different segments of the population. Lenders increase credit limits of customers who use relatively large amounts of credit and pay promptly or decrease credit limits of customers who make late payments. Lenders do not consider demographic characteristics in lending decisions because the ECOA of 1974 prohibits consideration of personal attributes such as age and marital status in lending decisions.

Generally speaking, the supply of revolving credit in a county relies heavily on the credit risk of its residents, as measured by their credit scores. Higher credit scores indicate a lower probability of default and hence allow for greater credit limits. To assess whether a county's beta has any impact on the level of revolving credit supply after controlling for its credit score, we include only beta and credit score as explanatory variables in Model 4. The coefficient of .02 for *Score* indicates that a one standard deviation increase in credit score for 2005 increases the level of revolving credit line per account for 2006 by around $740[1]. This change is statistically significant with a *t*-statistic of 32.73 and economically significant considering the average revolving credit line of $6,868 for 2006. Importantly, the effect of beta on the supply of credit is still statistically significant, but its economic impact has been reduced as indicated by the lower coefficient value of .119 compared to .168 in Model 1.

Our all-inclusive specification is represented by Model 5. The positive and significant values for *Unemployment Rate* and *Uninsured* are counter intuitive, perhaps because local economic conditions affect payment performance. Therefore, in Model 6, we include all the variables of Model 5 but *Score*. The signs of the coefficients for *Unemployment Rate* and *Uninsured* conform to theoretical predictions – a county with a higher unemployment rate and larger percentage of uninsured population is likely to have lower level of supply of credit. Our objective is to assess the effects of credit risk score and covariance risk on credit supply after controlling for the local economic conditions and demographic characteristics. Model 7 includes all the variables of Model 5 except *Unemployment Rate* and *Uninsured*. As reported, the output of Model 7 is similar to that of Model 5.

Overall, the findings suggest that local economic variables such as the *Income per Capita* and *Employ-Ment Concentration* have a negative impact while middle age groups (25-44, 45-64) and singles have a positive impact on credit supply for the next year. While a county's covariance risk is statistically significant, it has very little effect on credit supply.

6.2.2. Using the change in credit supply. Table 5 provides the results of OLS analysis based on equation (5). In Model 1, the regressors are related to previous year's credit supply, covariance risk, change in credit score, and an interaction term of covariance risk and change in credit score. For Models 2 and 3, we update Model 1 specifications by including local economic and demographic characteristics variables, respectively. Finally, Model 4 is an all-inclusive specification.

Table 5. Change in supply of revolving credit for year 2006 and beta

	Model 1	Model 2	Model 3	Model 4
Beta	-0.047*** [-3.71]	-0.031** [-2.35]	-0.052*** [-3.82]	-0.036** [-2.44]
Credit Supply (2005)	0.128*** [18.39]	0.097*** [9.55]	0.130*** [15.79]	0.097*** [9.39]
Change in Score (2005)	0.006** [2.52]	0.007** [2.52]	0.006** [2.03]	0.007** [2.55]
Beta × Change in Score (2005)	-0.005** [-2.12]	-0.007** [-2.39]	-0.006** [-2.16]	-0.007*** [-2.65]
Income per Capita (2005)		0.011*** [6.08]		0.012*** [6.27]
Annual Income Growth (2005)		0.153 [1.16]		0.074 [0.57]
Employment Concentration (2005)		-0.102 [-0.43]		-0.049 [-0.21]
Unemployment Rate (2005)		0.183 [0.48]		-0.054 [-0.13]
Uninsured		0.643*** [3.85]		0.675*** [3.56]

[1] The average and standard deviation of credit score for year 2005 were 659 and 37, respectively, for 3,140 counties.

Table 5 (cont.). Change in supply of revolving credit for year 2006 and beta

	Model 1	Model 2	Model 3	Model 4
Age less than 14 (2005)			0.073 [0.23]	-0.665* [-1.89]
Age 15 to 24 (2005)			0.441 [0.92]	0.524 [1.10]
Age 25 to 44 (2005)			0.036 [0.14]	0.172 [0.66]
Age 45 to 64 (2005)			-0.639 [-1.46]	-1.051** [-2.44]
Singles			0.571** [2.01]	0.276 [0.93]
Divorced			1.389*** [2.75]	1.327** [2.57]
Population Density (2005)			0.006 [1.05]	-0.005 [-0.78]
Intercept	-0.506*** [-11.08]	-0.704*** [-7.81]	-0.633*** [-3.08]	-0.583*** [-2.81]
N	3136	3132	3133	3131
Adjusted R^2	0.20	0.22	0.22	0.24

Note: The dependent variable is the change in revolving credit line per revolving account (in $1,000s) for the year 2006. Most of the independent variables are for year 2005, except *Uninsured*, *Singles*, and *Divorced* which are for year 2000. *Beta* is calculated using the level of monthly bankruptcy data from 1999 to 2005. The *t* values are in brackets below the coefficients, and are based on the robust standard errors. Detailed description of variables is given in Table 2. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. *N* stands for number of countries.

Our objective was to determine if for a given change in credit score, a county with a relatively high level of beta actually received a smaller supply of credit. Therefore, we need to focus on the coefficient of the interaction term. For exposition, consider a county *j* that experienced an increase in credit score by 3 points during 2005. Suppose in 2006, that county's revolving credit line per account increased by $297, the average of 3,136 counties (Table 2). Assume that if some unknown exogenous shock had taken place in 2005, then it would have made county *j*'s change in credit score equal to 8 points. Therefore, the net increase in the change in credit score for *j* is 5 points, equal to one standard deviation[1]. Also, let the covariance risk ($Beta_j$) be .90, which is the average beta based on the monthly data from 1999-2005 (Table 1). As per Model 4 of Table 6, the new change in credit supply for 2006 for county *j*, due to this external shock, will be $301[2]. Now, suppose there is another county *k* which is identical to county *j* except its beta is one standard deviation above that of *j*. That is, $Beta_k = 1.41$. Due to our hypothetical shock, the new change in credit supply for county *k* will be $283. This shows that a county with a higher covariance risk receives smaller increases in credit supply in comparison with an identical county having a lower beta. The difference of $18 ($301-$283) is statistically significant at the 1% level, however, the difference may not be important given the average increase in credit supply is $297.

We also find an increase in a county's income per capita for the previous year increases the change in revolving credit supply for this year, which is intuitive. A higher level of income implies a greater ability to repay the debt, thus these counties will likely obtain additional credit in the future. The most reliable predictor of a county's change in revolving credit supply for a given year is the level of its credit supply for the previous year. A county that received a higher level of credit supply for the previous year is likely to obtain additional credit for this year. As shown in Model 4, the coefficient of .097 for *Credit Supply* indicates that a one standard deviation increase in the level of revolving credit supply in 2005 increases the change in credit line the following year by $115[3]. This increase has a large economic impact because the average change in revolving credit line per account for 2006 is only $297.

Finally, we repeat analyses as reported in Tables 4-6 using the bankruptcy beta values as obtained from the first-difference in bankruptcy rates (equation (2)). We find quantitatively and qualitatively similar results as reported in Tables 4-6. Additionally, we also conduct analyses as reported in Tables 4-5 using four other measures of credit supply. These are revolving credit limit per consumer, revolving debt per account, revolving debt per consumer, and

[1] For 2005, the average and the standard deviation of the change in credit score are 2.61 and 5.00, respectively for 3140 counties.

[2] More precisely, it is $[.297 + 5 \times (0.007 - .007 \times .90)] \times 1000$.

[3] The average and standard deviation of revolving credit supply of 3,136 counties for 2005 is $6,571 and $1,182, respectively.

number of revolving accounts per consumer. In all cases, we find qualitatively similar results to the ones reported in the paper[1].

Conclusions

A county's bankruptcy rate conveys information on the investment returns on lending to consumers in a county. The covariance of a county's bankruptcy rate with those of other counties reflects the county's contribution to portfolio risk. Applying this insight, we compute county-level "bankruptcy" betas, market model coefficients on national bankruptcy rates. We find considerable heterogeneity in betas across counties, which is in part explained by local economic conditions and demographics. Data on local economic conditions are not collected very frequently and are not published on a timely basis. Our approach, which accounts for covariation of local markets with aggregate economic data, offers a method to assess performance of accounts in local markets on a more frequent basis.

We find that lenders appear to consider the information conveyed by bankruptcy betas, our measure for covariance risk, in offering revolving credit. Bankruptcy betas' estimated effect on credit supply is quite small, however. The small estimated supply effect suggests the possibility that consideration of covariance risk enables lenders to account for portfolio risk in account acquisition and management. Aggregate county-level data are readily available to implement this portfolio approach.

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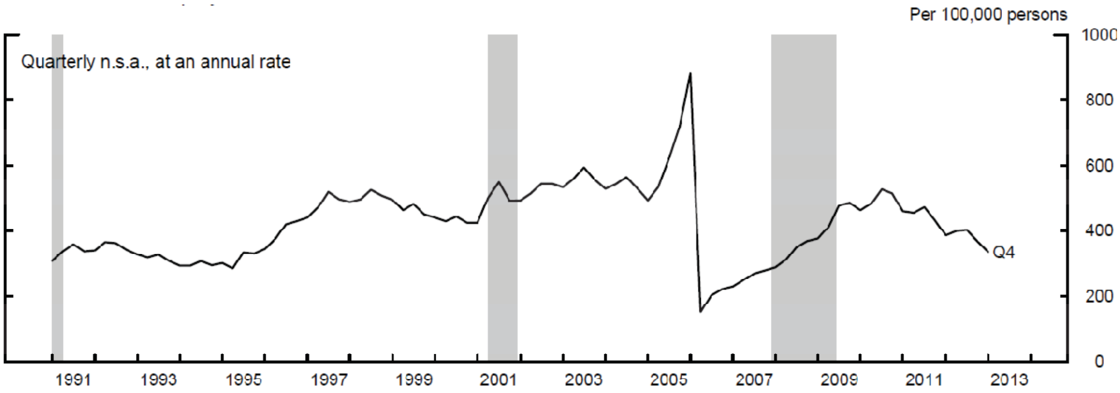
[1] These additional tables are available from the authors upon request.

Appendix



Source: Administrative Office of the US Courts.

Fig. 1. Consumer bankruptcy filings (1991-2012)

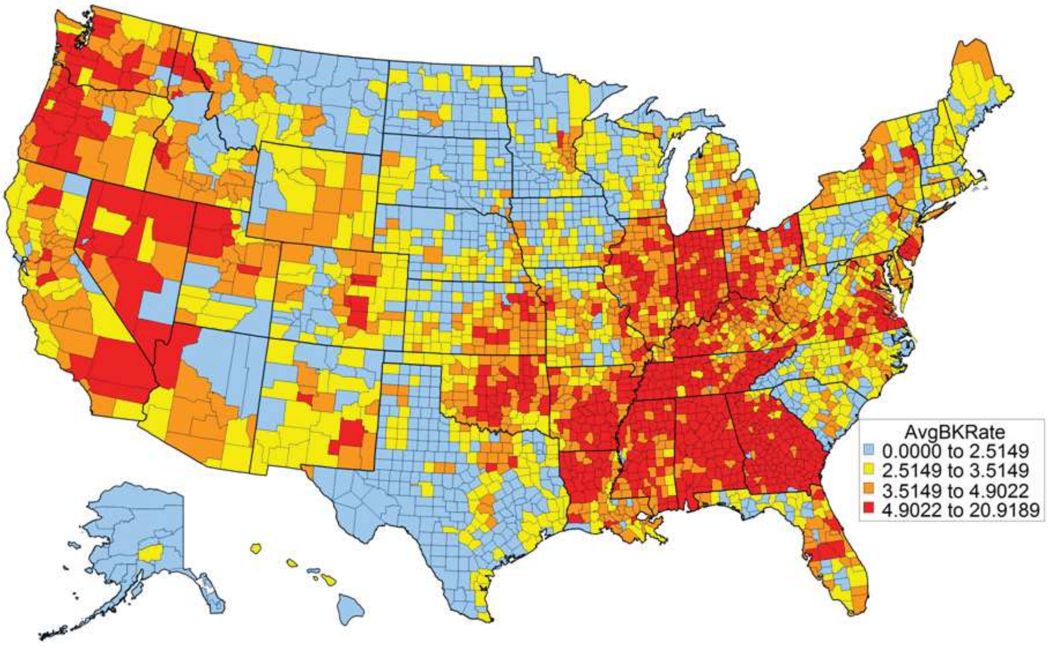


Fig. 2. Distribution of average bankruptcy (*BKR*) rate for period of 1999-2006

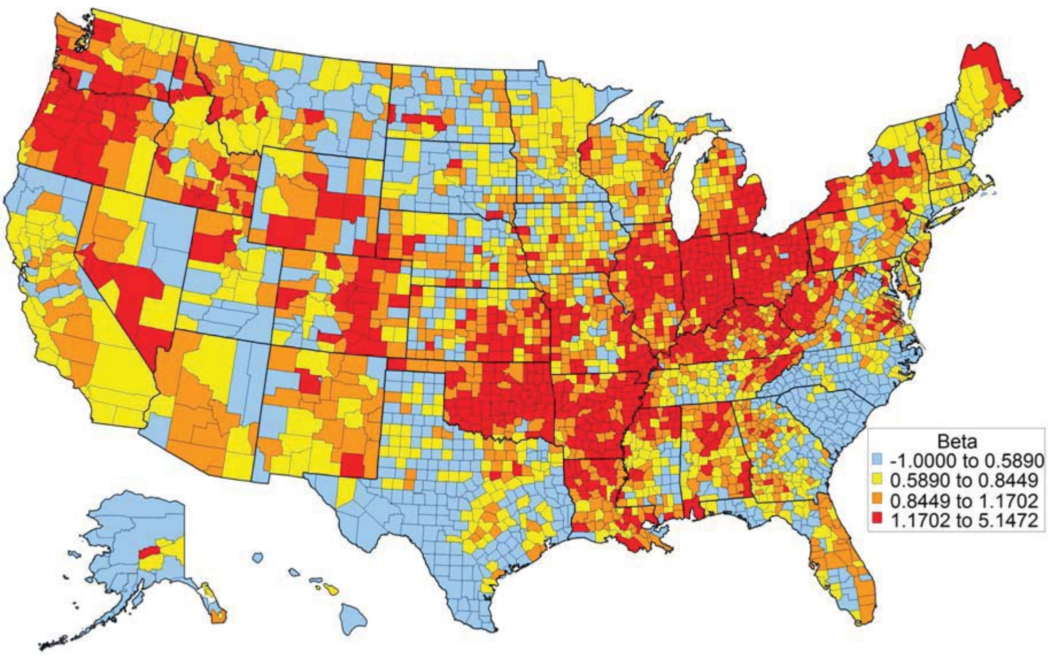


Fig. 3. Distribution of bankruptcy beta based on the level of bankruptcy rates

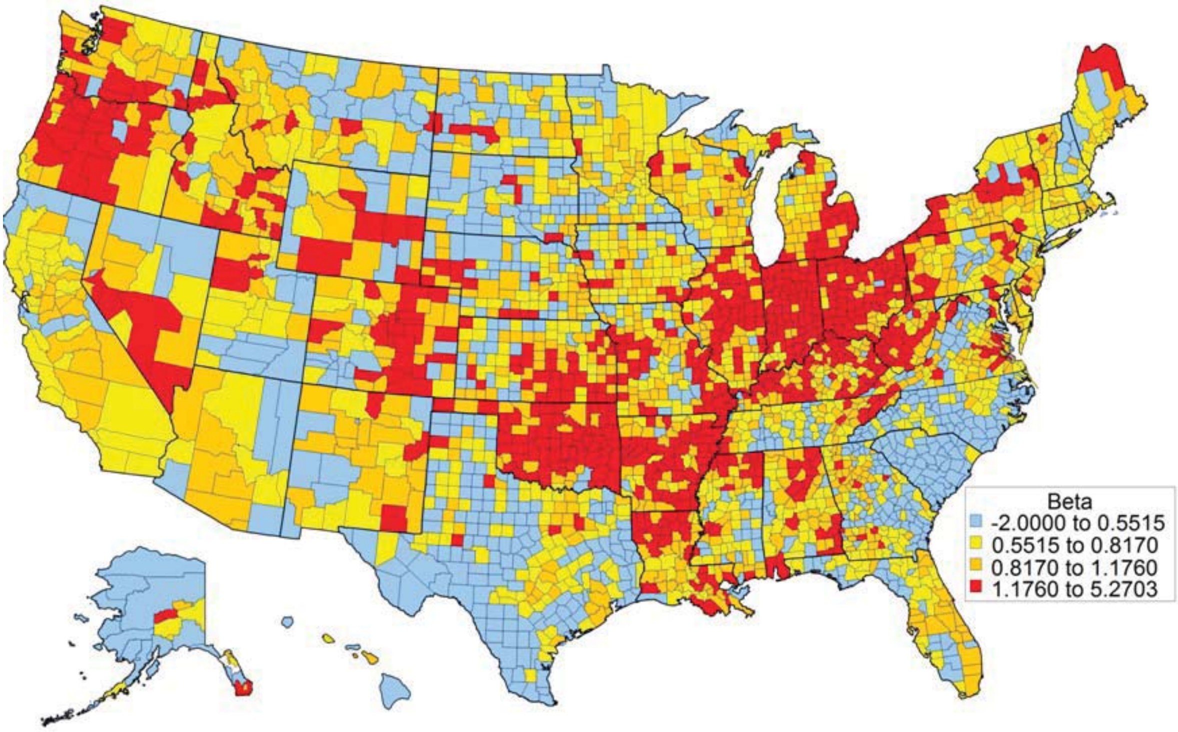


Fig. 4. Distribution of bankruptcy beta based on the first-difference of bankruptcy rates