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The Impact of Systematic Bankruptcy Risk on Household Lending in Local Markets

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Abstract

The recent collapse of the subprime mortgage markets in the U.S. has clearly demonstrated that consumer and mortgage lenders need to develop better tools to manage credit risk. This research empirically investigates the contribution that county-level personal bankruptcy filing data may have on risk assessment models for consumer credit. The paper extends the previous literature of county-level bankruptcy filing rates by using a capital asset pricing framework to investigate the relationship between county bankruptcy rates and U.S. aggregate bankruptcy rates. The findings show considerable variation in correlations across counties. The variation in correlation is not caused by differences in the level of bankruptcies or differences in the ability to predict accurately. While many of the fundamental factors that explain county-level bankruptcies have a similar effect on the correlation with aggregate bankruptcies, some factors have no effect or opposite effects. The empirical evidence indicates that estimates of local-level correlations in bankruptcy filings provide additional information for risk reduction in geographically diversified portfolios. This knowledge would be useful to consumer lenders for improving models for managing portfolio risks, setting credit policies and targeting borrower solicitations.

The Impact of Systematic Bankruptcy Risk on Household Lending in Local Markets

I. Introduction

Consumer credit in the U.S. hit a record high in February 2008 with more than $2.5 trillion in outstanding loans.[1] Over the past decade, the rising level of household credit was closely followed by dramatic increases in personal bankruptcy filings. In 2005, personal bankruptcy filings peaked at 2 million households before falling in 2006 due to major changes in the bankruptcy law.[2] Despite legal reforms making it harder for consumers to avoid repaying debt, on an annualized basis in the second quarter of 2007, one of out every 136 American families filed for bankruptcy.[3] These simple statistics and the recent subprime mortgage debacle clearly demonstrate that commercial banks and other types of lenders need to develop improved risk assessment tools to mitigate the effects of similar market meltdowns in the future. The practice of securitizing debt and marketing mortgage-backed bonds to investors around the globe only transferred the risk off the originators' balance sheets but did little to mitigate the economic damage from loan default.[4]

This paper empirically investigates the potential contribution that county-level personal bankruptcy filing data in the U.S. may have on risk assessment models for consumer credit. The benefits for lenders from geographic diversification in household lending are well recognized. While the correlation among asset returns is a standard measure of risk in finance and widely employed, the determinants of those correlations are much less understood. In fact, the available

[1] Federal Reserve [2008].
[2] American Bankruptcy Institute [2008].
[3] National Bankruptcy Research Center [2007].
[4] Nadauld and Sherlund [2008] found that diversification measured by covariance in state housing market returns was not significantly related to share of mortgage securitizations that were investment rated (or the cost of funding). They found a small effect for geographic diversification, but geographic diversification was not very closely related to and therefore not a good substitute for the covariance in housing returns.

evidence on the correlation of risks or returns in household lending is quite limited to date.[5] The lack of knowledge is problematic for both institutions and the market which have strong financial interests in properly balancing loan portfolio risks and returns. This paper provides evidence there is wide range in county-level correlations in bankruptcy, which suggests that there may be large unexploited opportunities for diversification.

II. Bankruptcy Prediction and Filings in the United States

Bankruptcy prediction at the individual level has achieved sufficient accuracy to be commercially viable. Models for predicting aggregate filings at local or regional levels have recently become available with the development of credit bureau-based databases that provide geographically disaggregated data on households' credit use and payment behavior. In previous papers, Trans Union's TrenData database was used to explore the benefits of greater disaggregation. The TrenData contains county-level aggregate variables for a series of large, nationally representative samples of U.S. consumers. This information is an ideal tool for benchmarking portfolio performance and for explaining the variability in credit payments. The findings show county credit use data substantially increase the percentage of explained variation in bankruptcy filing rates over more aggregated data.[6] Thus, models that forecast bankruptcy and payment performance with greater levels of geographic disaggregation provide more accurate benchmarks for evaluating portfolios than the aggregate models. For lenders, this information could be very valuable in making timely forecasts useful for managing portfolio risk, setting credit policies and targeting credit solicitations.

As highlighted above, there have been some notable trends and changes in U.S. bankruptcy

[5] To the best of the authors' knowledge, the recent paper by Musto and Souleles [2006] is the only existing study that considers the effect of correlation in risks in household lending. They estimate the correlation of individuals' expected probability of default with the aggregate probability. Then Musto and Souleles use this information to analyze the effects of the individual correlation and credit risk score on the distribution of credit to individuals.

[6] Barron, Elliehausen, and Staten [2000a] used county-level models to test hypotheses about the effect of declining stigma on the rise in consumer bankruptcies in the 1990s. Employing county-level models, Barron, Staten, and Wilshusen [2002] estimated the effects of casino gambling on local bankruptcy rates.

filings. The annual volume of personal bankruptcy filings more than doubled between 1990 and 2004, rising from 718,107 filings in 1990 to 1,597,462 filings in 2004 (Chart 1).[7] Bankruptcy petitions increased sharply in 2005 to 2,039,214, a 28 percent increase over the previous year. This rise was likely stimulated by a perception that the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005 would make going bankrupt less advantageous for consumers in the future. In fact, bankruptcy petitions plummeted to 617,660 in 2006. This precipitous decline in bankruptcies suggests the new law did cause some consumers to accelerate decisions to file for bankruptcy before the new law took effect on October 17, 2005. It may also have deterred consumers from choosing bankruptcy starting in 2006 as a remedy for their financial problems.

A striking statistic on the rise in consumer bankruptcies between 1990 and 1998 is that more than one of every twenty households in the nation filed for bankruptcy.[8] Losses to creditors from personal bankruptcy (i.e. debts discharged through bankruptcy proceedings) in 1998 alone exceeded $45 billion. This dramatic growth in personal financial failures occurred against the backdrop of one of the most favorable economic climates since the end of the World War II. The paradox of soaring bankruptcies coincident with extraordinarily low unemployment and strong income growth stimulated research on the determinants of bankruptcy (See for example: Fay, Hurst, White [1998]; Gross and Souleles [1998]).

Underlying the aggregate statistics are substantial cross-section variations in the number of bankruptcy filings and the change in bankruptcy petitions over time. Filing rates, defined as the number of bankruptcies per 1000 households, also vary widely across counties. Among the top ten percent of U.S. counties ranked by population, for instance, bankruptcies in 1997 ranged

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[7] Other measures of debt payment performance also deteriorated over this period. See, Elliehausen, *Monthly Statements* (various issues).

[8] It should be noted that the first subprime mortgage market collapse in the U.S. was during the period 1997-1999. Unfortunately, creditors made many of the same mistakes in judging credit risk a decade later.

from a low of 5.2 filings per 1,000 households in Montgomery County, Texas (a Houston suburb) to 50.3 filings per 1,000 households in Shelby County, Tennessee which contains the city of Memphis. As reported in Chart 2, the filing rate of 5.2 per thousand households for the lowest county was less than half of the average for all counties, and the rate of 50.3 in the highest county was nearly four and a half times greater than average. Overall, bankruptcy filing rates in the most populous counties were over 25% greater than filing rates for all counties. Clearly, cross-section differences in bankruptcy filing rates are substantial. These differences increase the value of a local-level forecasting tool.

As mentioned, previously cited research shows that consideration of county-level data on credit use produces a substantial improvement in prediction of bankruptcy filing rates over reliance solely on county-level data on income and other demographic variables associated with events that may trigger financial distress. Credit use variables alone explained about a fifth in the variation in county filing rate. Together with the other variables, credit use variables produced more than a threefold increase in the percentage of explained variation in filing rates over the model containing only the other variables. Such findings clearly show the value of geographically disaggregated data on credit use.

Not surprisingly, county bankruptcy rates also change at different speeds as local economic conditions decline or improve over time. Among the 16 counties with the highest bankruptcy rates in 1997, for example, the mean annual change in bankruptcy rates between 1992 and 2004 ranged from -1.5% to 8.3% (see Table 1). The mean annual change in bankruptcy filings also varied considerably during this period. Around the median county bankruptcy rate, the mean annual change in filings ranged from -3.2% to 7.3%. For the lowest rate counties, the mean annual change ranged from 2.7% to 7.8%. The variation in rates of change is even larger when smaller counties are considered. Overall, the mean annual change in bankruptcy filing rates ranged from -59.3% to 214.0%. Differences in changes suggest that the variability in local bankruptcy rates may be a concern.

III. Data

The data for this study consist first of annual observations of county-level bankruptcy filings for 3,137 U.S. counties between 1994 and 2005. This information was supplemented with a set of variables found or hypothesized to influence county-level bankruptcy filing rates or their correlation with aggregate filings. These variables measure the following influences: income and expectations of future income; demographic characteristics of the population; state laws impacting bankruptcy decisions; the composition of household debts; and credit market, real estate, and employment conditions. Table 2 lists the variable definitions and the source of the data from which the variables were constructed. The following subsections briefly discuss these variables.

Income and Expectations for Future Income

By far most household debts are repaid on an installment basis with payments being made from future income. The level of income and expectations about future income therefore are important determinants of the ability to service debt. Current income is measured by county personal income per adult. Income squared is included to allow for the possibility that the effect of income is not linear. Bankruptcy filings may increase with income because credit use rises with income, but increases may be smaller at higher income levels because necessities account for a smaller share of income as income rises. Regional data from the University of Michigan Survey Research Center's "Survey of Consumer Attitudes" was used to measure consumers' assessment of their current financial situation and expectations for future income. The variables are the percentage of consumers who report that their current financial situation is worse than a year ago and the percentage of consumers who expect their income to fall during the next twelve months. The percentage of consumers whose current financial situation is worse than a year ago (or expected to be) should be positively related to bankruptcy filings. Conversely, the percentage of consumers expecting a decline in income should be inversely related to bankruptcy filings.[9]

Demographic Characteristics of Consumers

Financial difficulties leading to bankruptcy may arise from interruptions in income due to unemployment, unexpected medical expenses, or dissolution of the household. Thus, it is expected that higher unemployment rates, the lack of health insurance, and the higher percentage of adults who are divorced or separated would all positively contribute to bankruptcy filings. County population density, measured by number of households per square mile, enters the model as a proxy for stigma. Larger population concentrations imply greater anonymity, which reduces the likely loss in reputation from filing for bankruptcy. Race is included because it has been shown to be correlated with asset holdings and wealth (see Kennickell, Starr-McCluer et al. [2000]).

Consumers use credit more heavily in early stages of the household life cycle than in later stages. Therefore, geographical areas with greater percentages of the population in early life-cycle stages (ages 25 – 44) and greater percentages of children (age less than 15) would use relatively more credit and should be more vulnerable to bankruptcy than other areas with older populations.

State Laws

Several provisions of state law influence consumer incentives to file for bankruptcy. Prohibiting wage garnishment (court ordered deductions from salary for the payment of debt) eliminates an incentive to seek relief from creditors by filing for bankruptcy. Larger amounts of

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[9] Consumers tend to use more credit when they are optimistic about the future. Consumers are generally reluctant to use credit to smooth consumption when faced with fluctuations in income and tend to postpone expenditures using credit when they <u>expect</u> a fall in income. For discussion, see Katona [1975].

homestead protection for real estate and other property exemptions protect more assets from creditors in a forced sale to satisfy unpaid debt and therefore reduce the incentive to file for bankruptcy.

Credit Use

The incidence of borrowing, debt level and types of credit used obviously influence the decision to file for bankruptcy. The incidence of debt is measured by the ratio of the number of borrowers to households and the level of debt by amounts of consumer (non-mortgage) and mortgage debt per borrower. Counties with higher ratios of borrowers to total households and higher debt levels per borrower are hypothesized to have higher bankruptcy filing rates.

Other credit-use variables in the model are the number of revolving accounts per borrower, the percentage revolving credit utilization (revolving debt / aggregate credit limit), and the percentage of accounts that were opened in the last 12 months. These variables provide information about the borrower's capacity to service debt. The inclusion of the number of revolving accounts (in addition to the variables that measure total debt) is a proxy for the average level of risk of the population of debtors in the county, as reflected by creditor supply decisions. Creditors view individual credit files to assess individual risk and make their lending decisions accordingly. A decision to extend a revolving line with a lower limit signals a creditors' assessment that the borrower is riskier, relative to a second borrower who received a higher limit. Consequently, an increase in the number of accounts in an area, holding constant the total amount of household installment debt, implies a riskier population and higher likelihood of bankruptcy (Bizer and DiMarzo [1992]). Higher revolving utilization rates signal that borrowers' unsecured debt levels approach what creditors consider a maximum capacity for servicing debt. Consequently, higher utilization signals greater vulnerability to exogenous financial shocks, and greater bankruptcy risk. The percentage of accounts opened in the last 12 months reflects new additions to debt. After an initial period of seasoning, a percentage of new accounts will experience delinquencies. Other factors held constant, it is expected that a greater percentage of new accounts will be associated with higher bankruptcy filings.

Credit and Real Estate Market Conditions

Several variables account for the macroeconomic conditions in credit markets. Two variables from the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices measure credit underwriting standards. One measure is the net change in banks' tightening credit standards for residential mortgages. The other variable measures banks' willingness to make consumer installment loans to households.[10] The level of interest rates are accounted for using the one-year constant maturities Treasury rate. Increases in the market interest rate reduce borrowing demand by households, which may result in a lower number of bankruptcies. To capture changes in overall prices, the percentage change in the consumer price index was employed. The impact of local real estate values on the accumulation of home equity is measure by the home price index. Greater home equity should discourage bankruptcy filing because when a borrower files for Chapter 7 bankruptcy, the court appointed trustee may sell the home and use the equity to satisfy unpaid debts.

IV. Estimates of Systematic Risk in County-Level Bankruptcy Rates

One of the basic principles of financial economics is that risk of a given asset should be measured in conjunction to the risk of a diversified portfolio. The incremental risk an asset contributes to a portfolio depends on the correlation of the asset's return with that of the portfolio. Assets have two types of risk. Systematic risks are risks due to market or macroeconomic factors that affect all assets. Unsystematic risks are risks that are unique to individual assets. Systematic risks are unavoidable, but unsystematic risks can be diversified

[10] The survey is a quarterly survey of approximately 60 large domestic banks and 24 U.S. branches and agencies of foreign banks. Questions cover changes in the standards, loan terms, and perceived demand for commercial and household demand for loans. See the web site www.federalreserve.gov/boarddocs/SnLoanSurvey/ for information.

away in a portfolio. If an asset's returns are not highly correlated with those of a portfolio, then the asset contributes relatively little risk to the portfolio. Thus in a credit context, loans to consumers in counties where bankruptcy filings are not highly correlated with overall bankruptcy filings would add little additional risk to a lender's portfolio and may actually reduce total portfolio risk.

The capital asset pricing model provides an appropriate methodology for measuring county-level bankruptcy risk. A county's bankruptcy risk can be measured by the slope of a regression of the county bankruptcy filing rate on the aggregate bankruptcy filing rate. That is,

$$r_{it} = \alpha_i + \beta_i r_{Mt} + \varepsilon_{it} , \qquad (1)$$

where r_{it} is the bankruptcy filing rate for county i for period t, and r_{Mt} is the aggregate bankruptcy rate. The regression coefficient, β_i , is an index of systematic risk, which indicates how the county bankruptcy rate covaries with the national aggregate rate. Coefficients greater than one indicate greater volatility i.e. that county bankruptcy rates increase by a greater percentage than the national aggregate rate. Coefficients less than one indicate that county bankruptcy rates increase by a smaller percentage than the national aggregate rate.

Beta is estimated by OLS regression using annual observations of bankruptcy filings from 1994 to 2004. Estimated β_i are widely distributed, ranging from -7.041 to 7.340 (Table 3). The median value of beta, 1.082, indicates that bankruptcy filing rates in a little more than half of counties rise or fall more than proportionately than aggregate bankruptcies. Ten percent counties have betas less than 0.432, and a quarter of counties have betas less than 0.730. These latter two sets of counties contribute less than average bankruptcy risk to diversified portfolios.

V. Predictions of County-Level Bankruptcy Rates

The model in this paper is an extension of Barron, Elliehausen, and Statens' [2000a] earlier model which explains county bankruptcy filings per 1,000 households as a function of the following variables: borrower income and expected income; demographic characteristics that influence the ability and willingness to use credit; the extent and depth of indebtedness; state laws that influence the economic incentives to file for bankruptcy; and credit and real estate market conditions. A population-averaged panel model (PAP) is estimated using the equation extension of the generalized linear model (Liang and Zeger [1986] and Zeger, Liang, and Albert [1988]). The model provides a response for a given explanatory variable that is directly estimated from the data without specific assumptions about the heterogeneity across individual counties in the population.[11] Bankruptcy filing rates are assumed to have a Poisson distribution with a first-order autoregressive correlation structure as county bankruptcy rates are directly correlated to prior filing rates.[12] Ultimately, the focus of the model should be on the bankruptcy predictions for individual counties. To evaluate the efficacy of the model, a R^2 statistic for each of the 3,137 counties was obtained by regressing actual filings on predicted filings. In order to assess the performance of the model over time, the R^2 for each year from 1994 to 2005 was also calculated.

Predictions by County

As reported in Chart 3, the R^2 statistics for individual counties vary widely. However, the frequency distribution of county R^2 is skewed to the left, with the R^2 for most counties being relatively high. Predictions for a relatively small number of counties were not very accurate. Nevertheless, for approximately half of the 3,137 counties, the model explains 73% or more of the variation in county bankruptcy filings (Table 4). And for 1,559 counties (three-fourths), the model explains over 50% of the variation in bankruptcy rates.

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[11] The PAP model describes how the average response across counties changes with the explanatory variables. In contrast, a subject-specific model would describe how an individual response for a given county changes with the explanatory variables. Although a subject-specific model would be desirable for predicting county-level bankruptcy rates, limited observations for each county make estimation of the county-specific component of responses difficult.

[12] Overall, the model explained 56 percent of the variation in county bankruptcy filing rates. A summary of overall regression results and effects of individual coefficients has not been included in this paper due to length restrictions. However, for interested readers, the table is available directly from the authors.

Predictions by Year

Regressions of county-level bankruptcy rates on predicted county-level bankruptcy rates by year indicate that county-level predictions for years 2000-2004 are better than predictions for 1994-1999. The explained variation in bankruptcy filings fell slightly from 46% in 1994 to a low of 43% in 1997 (Chart 4). Other studies attempting to explain bankruptcy rates experienced a similar deterioration in predictions during this period. Gross and Souleles [1998], for example, found a large unexplained increase in bankruptcies for this period after accounting for borrower risk and current economic conditions. They attributed this finding to a decline in stigma associated with the bankruptcy. Predictions improved after 1997, and from 2000, the percentage of explained variation in county bankruptcy filings exceeded 50 percent.

Beta and Predicted Bankruptcy Filings

Low values of beta do not arise solely because the predicted county bankruptcy filing rates are inaccurate, although some relationship does exist. A regression of county R^2 coefficients on beta indicates that county R^2 and beta are correlated. The coefficient for beta is positive and statistically significant. However the regression explains only about 28 percent of the variation in R^2. A considerable number of counties with relatively high R^2 values have low betas, and many counties with low R^2 values have high betas (Table 5).

Beta and predicted bankruptcy also are not different ways of measuring the same thing. A regression of the average predicted county-level bankruptcy filing rate on beta indicates that the predicted county filing rate and beta are positively correlated, but the regression explains only about a quarter of the variability in predicted bankruptcy filings. As discussed in the next section, further analysis provides evidence that bankruptcy filings and beta are capturing different information about bankruptcy risk.

VI. Determinants of Betas and Bankruptcy Filing Rates

To investigate why bankruptcy betas differ across counties, a regression of beta was run on the average value of the variables in Table 2 and standard deviations of variables that exhibited some variation over the 1994-2004 period. Another regression model was calculated of the average bankruptcy filing rate on the same set of explanatory variables. The results, shown in Table 6, suggest some variables that contribute to high bankruptcy filing rates also contribute to high betas. For example, variables indicating greater debt use (number of borrowers per households, number of revolving accounts per borrower, and revolving account utilization) are positively related to both beta and the bankruptcy filing rate. However, other variables are not consistently related to beta and average bankruptcy filings. Income is negatively related to beta but positively (and not statistically significantly) related to the bankruptcy filing rate. Pessimism and percent of households with a mortgage are positive and significantly correlated to beta but not the average bankruptcy filing rate. Density is not significantly related to beta but positive and significantly associated with the bankruptcy filing rate. Finally, the home price index is not significantly correlated to beta but negative and significantly related to the bankruptcy filing rate. Thus, beta captures different information about bankruptcy risk than the level of bankruptcy alone.

It is notable that for some variables greater debt use is associated with higher betas, but greater variability in these variables is associated with lower betas. One possible explanation for these results is that counties with persistently higher debt use may be especially vulnerable to financial distress and experience above average increases in bankruptcies when problems arise. In contrast, variation in debt use might reflect changes in households' expectations over the business cycle. If households rationally reduce debt use when they expect conditions to worsen in the future (Katona [1975], then they may be less vulnerable when conditions actually worsen. Hence, local bankruptcy filings rise less than proportionally to aggregate bankruptcy filings.

VII. Conclusion

The recent collapse of the subprime mortgage markets in the U.S. has clearly demonstrated that consumer and mortgage lenders need to develop better tools to manage credit risk. These tools are required not just for the initial credit granting decision but also for continuous monitoring of default risk for existing loan portfolios. Improving risk assessment models requires both better data and the development of new approaches to old problems. The purpose of this paper was to show that employing models with county-level bankruptcy data allows lenders to capture and utilize new predictive information that was not available previously with more aggregate bankruptcy statistics.

This paper employs the capital asset pricing model for assessing credit and bankruptcy risk in local geographic areas. A major advantage of this approach is that it does not require geographically disaggregated data on explanatory factors. Changes in key variables such county income, employment and population which are critical for predicting local bankruptcy filing rates only become available only after long delays. For example, the most recent county personal income data available is for 2006. The suggested framework here using forecasts of aggregate bankruptcies may be highly beneficial to lenders for generating local forecasts in targeting credit solicitations, setting credit policies and developing benchmarks for evaluating portfolios.

Betas measuring the correlations of individual county-level personal bankruptcy filing rates with the U.S. aggregate bankruptcy filing rate are computed to obtain an indicator of the systematic component of county bankruptcy risk. The range of estimated betas is large, from 7.340 to - 7.041. A substantial percentage of betas are relatively low. For instance, ten percent of betas are below 0.432, and 25 percent are below 0.730 -- suggesting diversification opportunities for reducing systematic risk.

Low betas are not simply an indication the bankruptcy filing rate is also low or that the bankruptcy filing rate cannot be predicted very accurately on the basis of economic and demographic characteristics. A regression of county R^2 coefficients on beta are correlated with county R^2 variables but not very highly. A considerable number of counties with relatively high R^2 values have low betas, and many counties with low R^2 values have high betas.

The empirical results indicate the determinants of the bankruptcy filing rate and beta are not identical. For example, income is negatively related to beta but positively (and not statistically significantly) associated with the bankruptcy filing rate; and the home price index is not significantly associated with beta but negative and significantly related to the bankruptcy filing rate. So beta provides different information about bankruptcy risk than the use of the level of bankruptcy alone and may be used profitably to manage risk in household credit portfolios.

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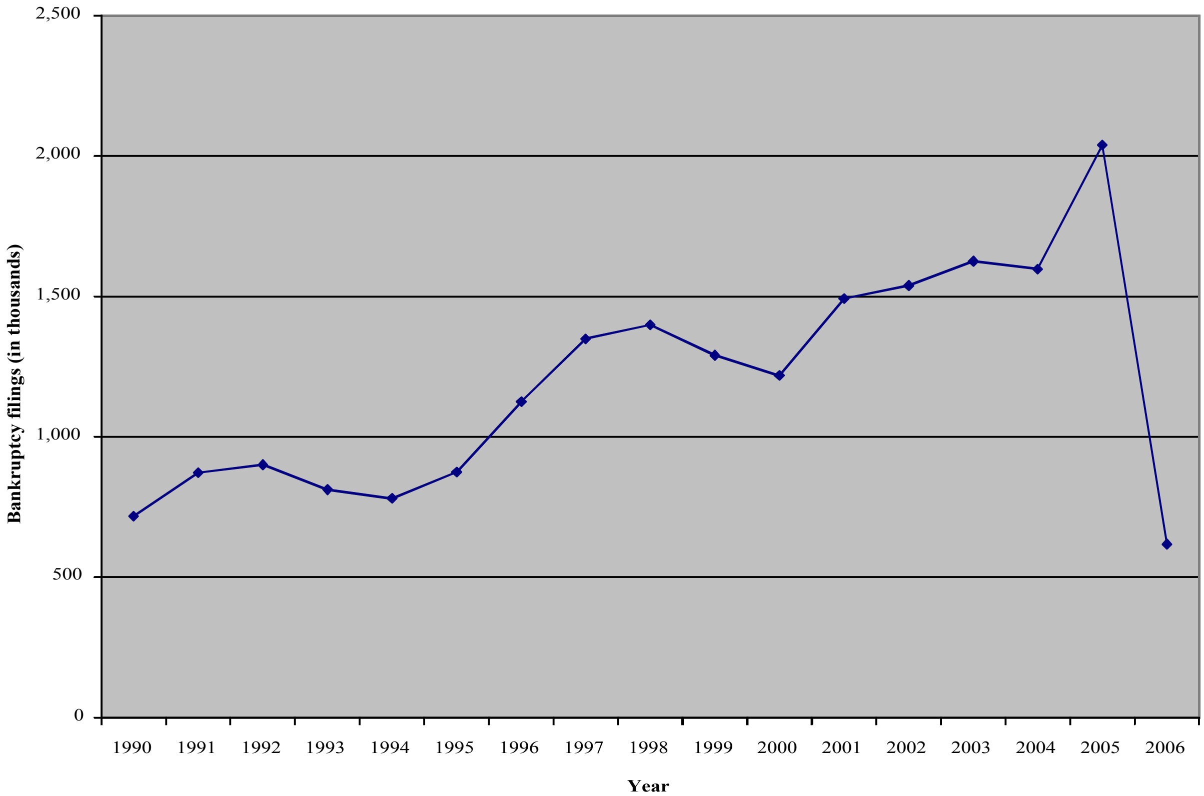
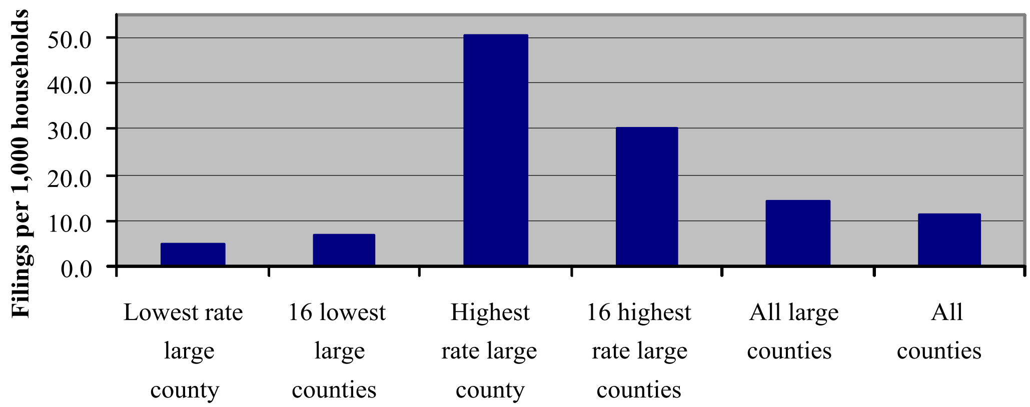
Chart 1: Personal (Non-Business) Bankruptcy Filings, 1990- 2006



Source: American Bankruptcy Institute

Chart 2: Variation in Bankruptcy Filing Rates among Counties



Source: Elliehausen [1999]

Chart 3: R-Squared by County

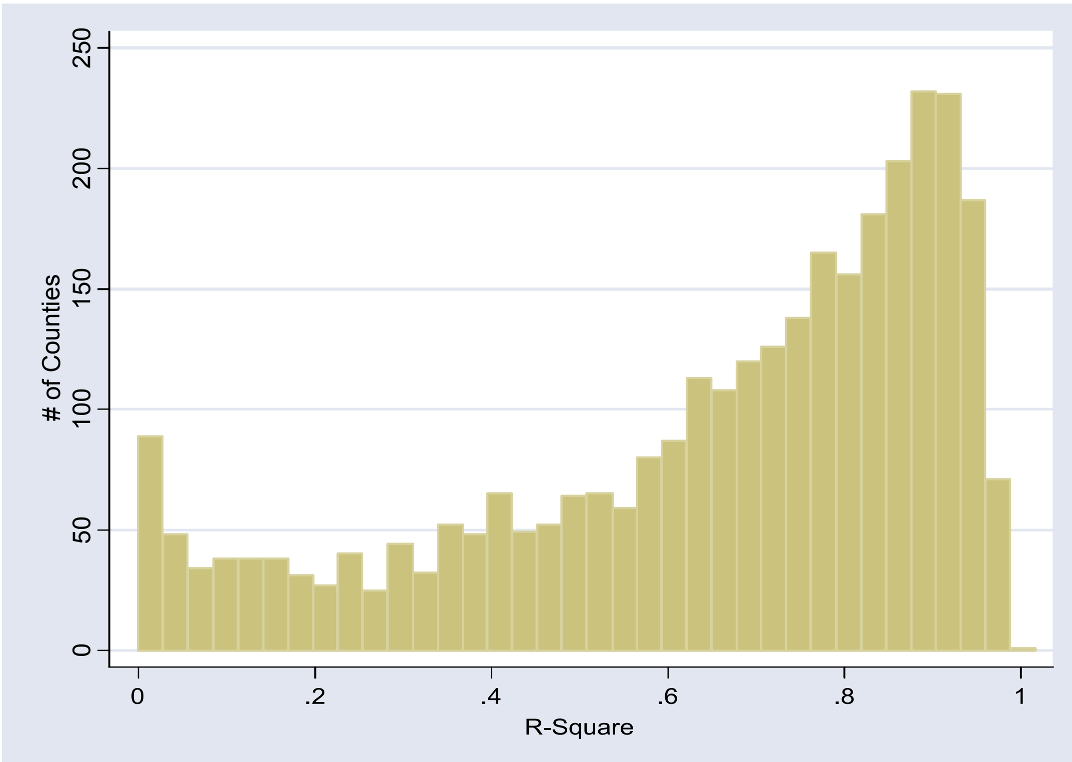


Chart 4: R-Squared by Year

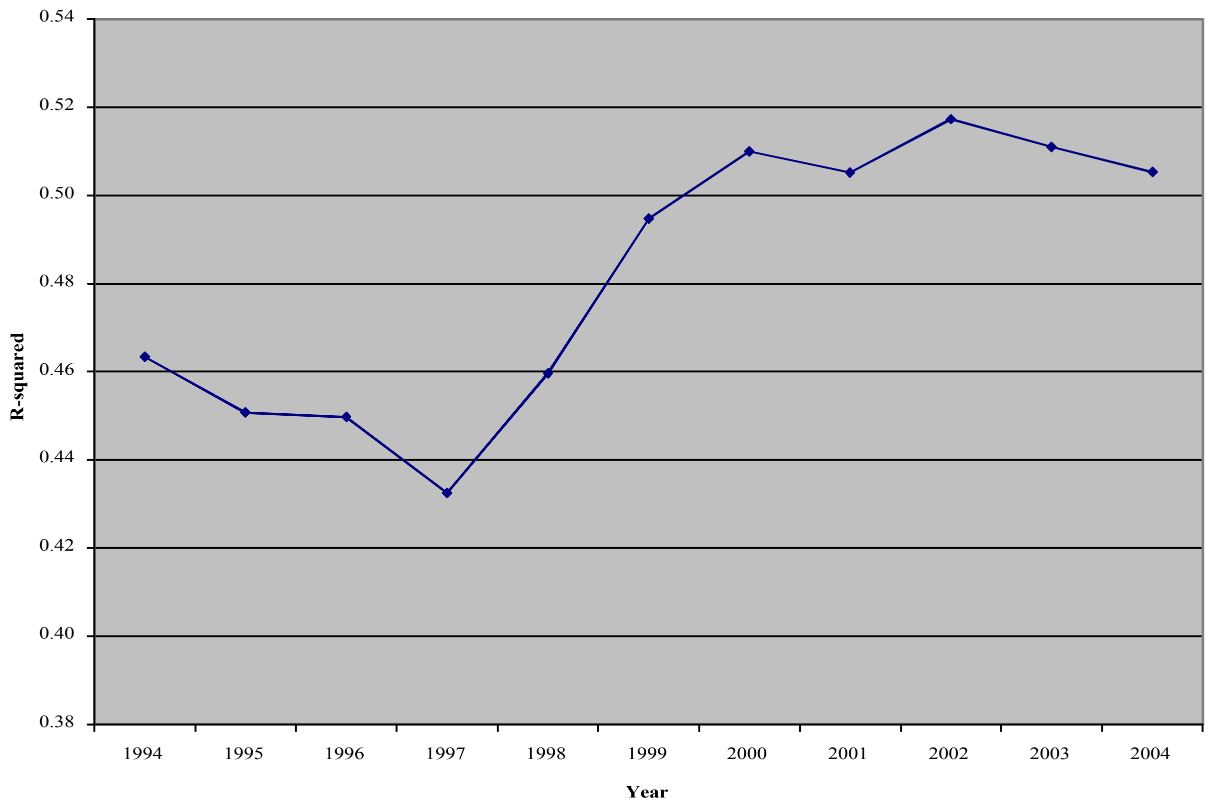


Table 1: Average Change in Bankruptcy Rates among Counties, 1992-2004

	Geometric mean change in bankruptcy rate		
	Minimum	**Average**	**Maximum**
16 large counties with highest bankruptcy rate	**-1.50%**	**3.35%**	**8.34%**
16 large counties with middle range bankruptcy rate (median)	**-3.20%**	**2.27%**	**7.31%**
16 large counties with lowest bankruptcy rate	**-2.70%**	**2.81%**	**7.77%**
All large counties (N=314)	**-6.05%**	**3.55%**	**12.61%**
All counties (N=3133)	**-59.34%**	**7.12%**	**214.01%**
Large county with the highest bankruptcy rate	**n.a.**	**2.69%**	**n.a.**
Large county with the lowest bankruptcy rate	**n.a.**	**2.32%**	**n.a.**

n.a. Not applicable

Table 2: Variable Definitions

Variable name	Variable definition (and source)
Bankruptcy filing rate	
Bankrupt rate	Number of bankruptcy filings per 1,000 households (Lundquist Consulting, SMR Research, US Census Bureau)
Income and expectation for future income	
Income	Personal income per adult (Bureau of Economic Analysis, Census Bureau)
Financially Worse	Percent of consumers who feel they are worse off financially than they were a year ago (Reuters/University of Michigan Surveys of Consumers)
Pessimism	Percent of consumers expecting income to fall in next 12 months (Reuters/University of Michigan Surveys of Consumers)
Demographic characteristics of consumers	
Unemp	Rate of unemployment (Bureau of Labor Statistics)
% Health UnIns	Percentage of population not covered by health insurance (Census Bureau)
%14less	Percentage of population less than or equal to 14 years of age (Census Bureau)
% 15-24	Percentage of population 15 to 24 years of age (Census Bureau)
% 25-44	Percentage of population 25 to 44 years of age (Census Bureau)
% 45-64	Percentage of population 45 to 64 years of age (Census Bureau)
% 65+	Percentage of population 65 years of age or older (Census Bureau)
% Black	Percentage of population that is black (Census Bureau)
% A or Am	Percentage of the population that is Asian or American native (Census Bureau)
% Hispanic	Percentage of the population that is Hispanic (Census Bureau)
Density	Households per square mile (Census Bureau)
% Divorced	Percentage of adults who are divorced (Census Bureau)
% Single	Percentage of adults who are singles i.e. never married (Census Bureau)
State laws	
Garnishment	% of wage garnishment (Agarwal et al. 2003)
Home	Amount of home value exempted (Agarwal et al. 2003)
Property	Amount of property value exempted (Agarwal et al. 2003)
Credit use	
Borr per HH	Borrowers per household (TrenData, Census Bureau)
Cons Debt	Consumer debt per borrower (TrenData)
% with Mortgage	Percentage of borrowers with mortgage debt (TrenData)
Mortgage Debt	Mortgage debt per borrower (TrenData)
Revolving Acct	Number of revolving accounts per revolving credit borrower (TrenData)
% Rev Utiliz	Percentage of revolving credit lines utilized (TrenData)
% of New trades	Percentage of new opened trades in the last 12 months (TrenData)
Consumer debt to income	Ratio of consumer debt per borrower to personal income per adult (TrenData, Bureau of Economic Analysis, Census Bureau)
Credit market, real estate, and employment conditions variables	
Mortgage Tighten	Percent of banks net tightening standards for all residential mortgages to households (Federal Reserve Board)
Consumer loan tighten	Percent of banks net tightening standards for consumer installment loans to households (Federal Reserve Board)
Interest	Interest rate on one year T-Bills of constant maturity data (Federal Reserve Board)
Home price index	Conventional mortgage home price index (Freddie Mac)
Change CPI	Change in Consumer Price Index (Bureau of Labor Statistics)
Industry employment (8 industries)	County employment in industry to adult population (Census Bureau)
Industry employment concentration	Sum of squared industry employment ratios

Table 3: Summary Statistics for County-Level Beta

Statistic	Beta
Mean	1.177
Minimum	-7.041
Maximum	7.340
Standard deviation	0.716
Percentile	
1st	-0.122
5th	0.256
10th	0.432
25th	0.730
50th	1.082
75th	1.541
90th	2.048
99th	3.404
Memo: Number of counties	3,139

Table 4: Summary Statistics for County-Level Predictions

Statistic	R-squared
Mean	0.651
Minimum	<0.0005
Maximum	0.989
Standard deviation	0.268
Percentile	
1st	0.003
10th	0.193
25th	0.497
50th (median)	0.734
75th	0.866
90th	0.924
99th	0.972
Memo: Number of counties	3,137

Table 5: Distribution of Beta by County-Level R-Squared Values
(Number of Counties)

	R-square									
Beta	0.200 or less	0.201 - 0.400	0.401 -0.550	0.551 -0.650	0.651 -0.725	0.725 - 0.800	0.801 - 0.850	0.851 - 0.900	Greater than 0.900	Total
0.450 or less	190	65	37	17	13	7	2	1	1	333
0.451 - 0.701	71	89	70	60	40	28	13	14	6	391
0.7 01 - 0.850	20	40	44	48	46	50	25	25	18	316
0.85 1 - 0.975	15	20	38	36	44	47	34	34	36	304
0.976 - 1.105	8	18	31	35	29	47	36	38	36	278
1.106 - 1.250	3	17	32	28	42	45	35	46	50	298
1.251 - 1.400	5	10	24	14	21	41	26	39	54	234
1.4 01 - 1.700	1	9	15	35	37	63	54	70	105	389
Greater than 1.700	5	12	18	39	36	63	79	125	217	594
Total	318	280	309	312	308	391	304	392	523	3,137

Table 6: Determinants of Beta and the Average Bankruptcy Filing Rate

	Dependent variable	
Explanatory variables	Beta	Bankruptcy filling rate
Income	-0.1099***	0.0253
Income-square	0.0012***	-0.0014
Income Variation	-0.0279**	0.0424
Financial Worse	-0.0032	-0.0788
Pessimism	0.0578***	-0.0286
Unemp	0.9573	-6.0282
Unemp Variation	-2.3836	-25.1043*
% Health UnIns	-0.4446	-3.5178
% Health Unins Variation	-3.2311*	-16.2730
% 14 less	4.5806***	10.3752*
% 15-24	2.3159***	8.4836*
% 45-64	-1.0525	-47.3294***
% 65+	1.3002**	-3.9023
% Black	1.3735***	14.9571***
% A or Am	-1.0738***	-6.9643***
% Hispanic	-0.5116***	-1.1483
Density	-0.0000	0.0003***
% Divorced	5.2718***	58.4966***
% Single	-2.3676***	-31.5103***
Garnishment	0.0144***	0.2058***
Home	-0.0000	-0.0000***
Property	-0.0000***	-0.0001***
Borr per HH	4.2029***	30.2050***
Borr per HH Variation	-4.5245***	-17.7030**
Cons Debt	0.0001***	0.0003**
Cons Debt Variation	-0.0000	-0.0004***
% with Mortgage	1.5092***	0.7228
% with Mortgage Variation	0.1952	-7.0014
Mortgage Debt	-0.0000***	-0.0001***
Mortgage Debt Variation	0.0000	0.0000
Cons. debt per income	-0.0021***	-0.0056*
Cons. debt per income - Variation ~n	-0.0005	-0.0023
Revolving Acct	0.3519***	2.5735***
Revolving Acct Variation	-0.7424***	-5.4178***
% Rev Utiliz	1.7002***	22.7995***
% Rev Utiliz Variation	-0.9095	-3.4176
% of New Trades	0.9952**	17.6574***
% of New Trades Variation	-0.1282	-0.5537
Home price index	0.0005	-0.0207***
Empl. Ratio - Mfg (31)	0.7218***	2.5353**
Empl. Ratio - Wholes~42)	0.5530	4.9744
Empl. Ratio - Retail~44)	0.8965*	1.7538
Empl. Ratio - Inform~51)	-0.2764	2.7427
Empl. Ratio - Real E~53)	1.3974	0.6854

Explanatory variables	Beta	Bankruptcy filling rate
Empl. Ratio - Prof. ~54)	-0.0534	-0.9422
Empl. Ratio - Admin.~56)	-0.8771*	0.9447
Empl. Ratio - Educ. ~61)	0.4988	-2.2739
Empl. Ratio - Health~62)	0.0626	-1.7169
Empl. Ratio - Arts &~71)	-1.0894	-3.8277
Empl. Ratio - Other ~81)	2.1246	-7.1328
Industry employment concentration	0.5586***	1.4277**
Constant	-1.2385	1.3687
N	3,135	3,135

Significance level: * p< .10; ** p< .05; *** p<.01