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Collective Behavior in Corporate Bankruptcies and Business Cycle

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Abstract

We investigate collective behavior in corporate bankruptcies and its relationship with business cycle. Using both model-generated and empirical data, we find that there exists collective behavior in firm bankruptcies and that such collective behavior is more prominent during expansions than recessions. Our simulation analysis in the agent-based framework further corroborates that business cycle is a significant explanatory variable that affects the magnitude of collective behavior in firm bankruptcies.

JEL classification: G33, E17, E32

Keywords: Collective behavior, Corporate bankruptcy, Business cycle, Power law distribution, Agent-based model

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1 Introduction

Failure of a firm has immediate negative effect on the welfare of its stakeholders. The collapse of one firm, however, could incur staggering collateral damage to the aggregate economy such as sudden unemployment hike because the effect of a single firm's default can be propagated through the network of creditor-debtor relationship, driving other firms into distress and/or bankruptcy (Fujiwara, 2004). Given the disastrous harm that can be caused by bankruptcy in numbers, understanding collective behavior in firm bankruptcies is vital to prescribing means of avoiding such disasters. We addresses the following two questions in this paper: First, "Does there exist collective behavior in corporate bankruptcies?" And second, "How does business cycle interact with such collective behavior if it exists?"

While corporate bankruptcy has been extensively studied in various contexts for more than several decades, the main interest has evolved around the assessment of the bankruptcy probability and its prediction. Since the first multivariate bankruptcy prediction model was developed by Altman (1968), the vast amount of research on bankruptcy prediction has been conducted using one of the three types of models prevailing in finance literature; i) accounting-based models, ii) market-based models and iii) hazard models.[1] Our work differs from the existing studies of corporate failure in that we are interested in the cross-sectional herding dynamics among bankrupted firms, which has received little attention both in academic research and in practice up to date.

The term collective behavior, first introduced by Park and Burgess (1921), refers to social processes and events which do not reflect existing social structure such as laws, conventions, and institutions, but instead emerge in a *spontaneous* way. It is driven by group dynamics, encouraging people to engage in acts that they might consider unthinkable under typical social circumstances (Locher, 2002). The existence of collective behavior in bankruptcies may indicate that bankrupted firms tend to make clustered actions and decisions conducive to their shared bankruptcies. In fact, collective behavior has been identified in increasing number of venues in the markets.

To explore collective behavior in corporate bankruptcies, we utilize the power law distributions to describe the behavior of bankrupted firms. The conformity to a power law distribution indicates collective behavior of agents in a certain system (Káptalan et al., 2011) because it implies that large objects account for a disproportionate share of overall activity and thus their tendency to act collectively without centralized direction. While power law distribution, also known as Pareto distribution, has been used to characterize the

[1] See Agarwal and Taffle (2008), Bauer and Agarwal (2014), and Altman et al. (2014) for review of relative efficacy of those models.

distributions of stock returns (Plerou et al., 1999), firm size (Axtell, 2001; Cabral and Mata, 2003; Kang et al., 2011; Ishikawa et al., 2013), and CEO compensation (Blackwell et al., 2015), our study is, to our best knowledge, is the first attempt to investigate collective U.S. bankruptcy behavior using power law distributions. After obtaining empirical evidence for collective behavior in bankruptcies, our investigation extends to simulation study to confirm the empirical finding and to further examine the relationship between the collective behavior and business cycle .

2 Hypothesis

Following the discussion in the previous section, we present three (potentially testable) predictions on the collective behavior.

- H_1: There exist collective behaviors in firm bankruptcies.
- H_2: Those collective behaviors tend to be stronger in economic expansions than in recessions.
- H_3: Business cycle is a significant explanatory variable which determines the magnitude of collective behaviors of bankrupted firms.

3 Data

Our data consist of empirical data as well as simulated data. All of our empirical data come from UCLA-LoPucki Bankruptcy Research Database (BRD), which includes approximately 200 fields of data on all of the large, public company bankruptcies filed in the United States Bankruptcy Courts since October 1, 1979. A company is considered "public" if it filed an annual report with the Securities and Exchange Commission (SEC) for a year ending not less than three years prior to the filing of the bankruptcy case. A company is considered "large" if its assets in the corresponding fiscal year's annual report are worth \$100 million or more, measured in constant 1980 dollars (about \$290 million in 2014 dollars). Coverage of BRD includes cases filed under both Chapter 7 and Chapter 11 whether filed by the debtors or creditors. While there are 1001 bankruptcy filings in total recorded in BRD between 1980 and 2014, we dropped the firms with missing data and financial firms to finally obtain 840 bankrupted firms.

Simulated data is all generated by an agent-based model (henceforth labeled ABM) following the original calibration of Gatti et al. (2005, 2007). Our data simulation consists of two parts. The first part is to examine whether the simulated data yields collective behavior of bankruptcies similar to the real data. Besides, the validity of the simulation framework of ABM will be determined at this juncture by comparing collective behaviors evidenced in the empirical and simulated data. The purpose of the second simulation assignment is to obtain a data set large enough to conduct ordinary least square (henceforth labeled OLS) regression analysis on the relationship between collective behavior and aggregate fluctuations. For the first simulation part, we calibrate the total simulation times equal to 57 with the first 22 periods discarded as burn-ins to match the empirical data length of 35 years. Also, we calibrate the total number of firms equal to 3500 to correspond to the number of bankrupted firms present in the real data. We repeat the simulation 100 times to ensure that the number of bankrupted firms from simulations match that from the real data in a stable manner. The average number of bankrupted firms in the 100 simulations is 836, quite close to 840 in the empirical data. When each iteration is completed, the bankrupted firms obtained are saved along with their assets, sales, and debts relative to which collective behavior is characterized. For the second simulation procedure, we set the total number of firms to 300,000, and the simulation periods to 150 with initial burn-ins equal to 60 (40% of total simulations). Thus we obtain approximately 2000 bankrupted firms in each period, which we use to estimate the power law exponent for the corresponding period using OLS. Iterating the simulation routine over the entire 150 period gives a complete set of data containing a series of scaling exponent estimates and growth rates of total output used as business cycle proxy, which will be used to estimate Eq. (4). This simulation procedure is repeated 100 times.[2]

Business cycle is classified based on NBER Recession indicators, which regards 1980, 1982, 2001, 2008, and 2009 as recessions. In our empirical data set, the numbers of bankrupted firms are 358 and 482 during boom years and recession years, respectively. The Hodrick-Prescott filter (HP filter) is used to determine the business cycle in our simulated data.

4 Methodology

4.1 Power law distributions

To capture firms' collective behavior, we use power law distribution in which the scaling exponent is interpreted as the magnitude of collective behavior (Káptalan et al., 2011). The power law distribution is usually

[2] At the start of each round of simulation, the number of firms is fixed. That is, when a firm goes bankrupt during simulation, the firm will leave the market and another firm will fill in at the beginning of the subsequent period.

specified via its counter cumulative density function ($P(x)$):

$$1 - F(x) = Pr(X > x) = P(x) = kx^{-\zeta} \tag{1}$$

for some $k > 0$. The power-law exponent ζ is independent of the units in which the law is expressed. The probability density function (PDF) is of the form:

$$f(x) = \begin{cases} \zeta k x^{-(\zeta+1)}, & x > k^{\frac{1}{\zeta}} \\ 0, & x \leq k^{\frac{1}{\zeta}} \end{cases} \tag{2}$$

Taking the logarithm on both sides of Eq. (1), we get a linear relationship:

$$Ln\,(P(x)) = C - \zeta Ln(x) \tag{3}$$

The standard error of ζ is asymptotically $\zeta\,(n/2)^{-1/2}$ for positively autocorrelated residuals caused by ranking procedure (Gabaix, 2009). We use Eq. (3) to establish an econometric model that can be estimated using linear regression, where ζ is the slope of the regression line and $P(x)$ is the counter cumulative frequency. The above specification will be used to calculate and compare the exponent estimates with both empirical and simulated data.

4.2 Agent-based Model

To further examine the collective behavior in bankruptcies with simulated data, we utilize an ABM proposed by Gatti et al. (2005, 2007). An attractive feature of ABMs in light of our study lies in their ability to generate an economy where *heterogeneous* firms interact with the banking system, thereby allowing indirect interactions among the firms themselves. Thanks to the heterogeneity in firm size, profit, credit demand, and “bad debt”, ABMs can produce, through simulations, complex real-world-like economies wherein firms attain varying levels of financial conditions and performances. Some firms could go bankrupt and leave the market as their financial conditions deteriorate while other firms stay profitable. If a firm goes bankrupt, however, not only aggregate output goes down, but also the banking system suffers a capital loss, which results in the shrink of credit supply and the rise of interest rates. Consequently, bankruptcy probabilities for the other firms will increase as competition for more credit becomes intense and other firms’ balance sheets worsen. Eventually, those firms on the verge of bankruptcy will default and bankruptcies will spread.

The ABM employed in this study can captures the domino effect that failure of a single firm can have market-wide effects including successive bankruptcies as the default of the firm propagates through a network of financial system.[3] This ability of the ABM to generate apparent clustering, or collective behavior in bankruptcies is vital to investigating our research questions for two reasons. First, we need to make sure that the simulated data obtained from our theoretical framework closely match the bankruptcy behavior in empirical data because it indicates that our theoretical model captures economic reality reasonably well. Second, after confirming the validity of initial simulated data, we explore the relationship between the collective behavior and business fluctuations using larger-scale simulations.[4]

4.3 Power law exponent and business cycle

After obtaining simulated data from our theoretical framework specified in the previous section, we investigate how business cycle affects firms' collective behavior in bankruptcies by implementing the following regression model:

$$\zeta_t = \phi_0 + \phi_1 \Delta_t + \varepsilon_t \ , \tag{4}$$

where ζ_t is the scaling exponent and Δ_t is the growth rate of total output used as business cycle indicator. The estimation results from the Eq. (4) will provide a more precise picture of the effect of aggregate fluctuations on the collective behavior beyond the differential effects of booms and recessions.

5 Results

5.1 The existence of collective behavior

Using OLS regression, we estimate Eq. (3) after adding a normally distributed error term to the equation. Each year (time), the log-cumulative frequency is regressed on the log of bankrupted firms' assets, sales, and debts, respectively. We implement the same OLS estimation twice with empirical data and simulated data. We find that bankrupted firms' assets, sales, and debts all follow power law distributions both empirically and theoretically. Table 1 shows that the power law exponents are remarkably similar not only across different proxies for firm sizes but also across the two different sets of data. Thus the scaling behavior in the size distribution of bankrupted firms seems to be quite robust. We take this finding also as evidence that the

[3]Thus the ABM in this study can be viewed as a financial accelerator model sharing the spirits of Greenwald and Stiglitz (1988, 1990, 1993).

[4]The detailed description of simulation procedures is available upon request.

ABM in our study is characterized well enough to generate artificial data consistent with the empirical data, serving as a reasonable approximation to the economic reality. This feature of our theoretical model plays a pivotal role in the analysis below.

[Insert Table 1 Here]

5.2 The differential effects of booms and busts

A novel feature of our study comes from the insight that macroeconomic fluctuations might influence firms' bankruptcy behaviors differently. We investigate this issue first by estimating Eq. (3) for booms and recessions separately. Figure 1 shows OLS regression results based on empirical data. First, bankrupted firms's assets, sales, and debts all follow power law distributions in both boom and recession periods. That is, the scaling behavior in the size distribution is still apparent for each phase of business cycle. Second, while point estimates of the power exponent are reasonably similar within each sub-sample, they are persistently and substantially different across booms and recessions. Notably, the power law exponents of boom years are significantly higher than those of recession years, which indicates that bankrupted firms show stronger collective behavior during booms. This result corroborates the existing studies such as Gaffeo et al. (2003). We present a plausible explanation for this finding in the next subsection.

[Insert Figure 1 Here]

5.3 Business cycle as an explanatory variable

We now attempt to substantiate the results obtained in the previous section. Based on the simulated data from the theoretical model, we estimate the power law exponents of bankrupted firms' assets, sales, and debts at each time. Also we calculate the growth rate of total output for each simulation period. We then perform OLS regressions for Eq. (4) using the growth rates as an explanatory variable serving a business cycle indicator. Table 2 shows that for all three proxies for firm size, the coefficient estimates for total output growth rates are significantly positive at 95% significance level. Consistent with the results in the previous section, this regression analysis demonstrates that the collective behavior tends to be procyclical and the business cycle has a significant explanatory power for collective behavior of corporate bankruptcies.

[Insert Table 2 Here]

Firms tend to make more investments during booms than recessions (Peters et al., 2014), pushing up credit demand higher in boom years. When firms are on the verge of bankruptcies during expansions, therefore, they may find it harder to get the credit they need because the competition for bank loans is likely to be stronger during boom years. Unlike mega-firms, relatively small firms, in particular, could suffer more during booms due to this fierce competition for credit such as bank loans. Furthermore, because of informational asymmetry smaller firms are more likely to suffer from fierce credit competition and higher interest rates (Vos et al., 2007), and hence more likely to fall into bankruptcy. More defaults of those relatively smaller firms tend to lead to more uneven distributions of assets, sales, and debts. The positive coefficient for growth rate of total product in Table 2 highlights this dynamics between firms' collective bankruptcy behavior and macroeconomic fluctuations.

6 Conclusion

In this study, we investigate collective behavior in corporate bankruptcies using the power law distribution and an agent-based model as analytical frameworks. We provide evidence that collective behavior in bankruptcies exists and is significantly affected by business cycle. The estimates of power law exponents from the empirical and simulated data are nearly the same across the different firm size proxies, which suggests that firms' collective behaviors in bankruptcies be quite robust phenomena, and the agent-based model is well suited for the analysis in this study. Our sub-sample analysis shows that the collective behavior tends to be stronger during economic expansions than recessions. The least-squares regression analysis further confirm that the collective behavior of the firms is pro-cyclical. We propose a possible underlying mechanism responsible for this finding in the theoretical framework of the agent-based model. The financial fragility of a bankrupted firm could be transmitted to other firms via dynamic interactions between firms and the banking system, causing not only aggregate fluctuations but also an apparent herd of bankruptcies in the market.

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Figures and Tables

Figure 1: Counter cumulative density function of firm size in the tail

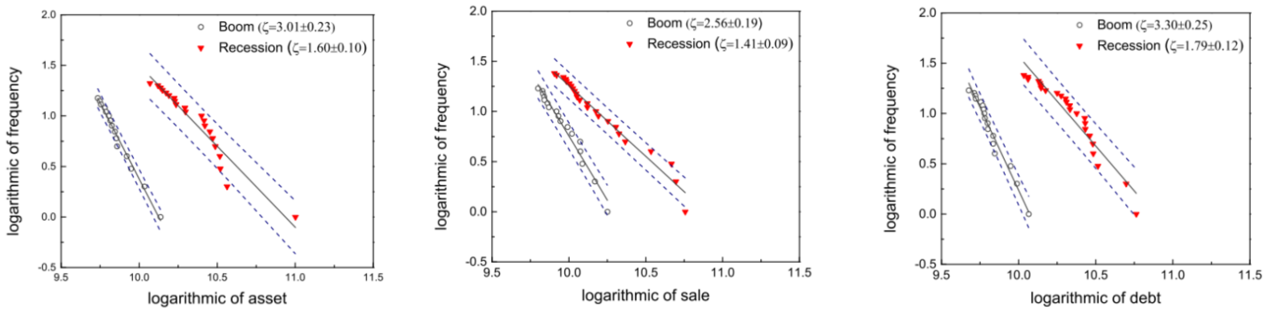

Table 1: Power-law exponents for bankrupted firms

	Empirical Results	Simulation Results
Asset	1.420 ± 0.069	1.451 ± 0.069
Sales	1.466 ± 0.072	1.381 ± 0.065
Debt	1.432 ± 0.070	1.456 ± 0.069

Table 2: Regression results for firm size and business cycle indicator

Regression Coefficient	95% Confidence Interval
Asset	$(4.535, 5.363)$
Sales	$(3.947, 4.680)$
Debt	$(4.547, 5.377)$