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The Market For Failure:
An Examination of Collective Knowledge Theory
and What Bond Markets Tell Us About
Corporate Bankruptcy Filings

Brandon L. Maslov*

ABSTRACT

The ability to predict how many large public companies file for bankruptcy protection per year is useful for understanding underlying reasons for economic turmoil. Most literature on the subject does not address aggregate filing frequency, but instead focuses, at a microeconomic level, on the reason why an individual firm files for bankruptcy. This Article, however, takes a macroeconomic approach to analyzing the issue. It examines the relationship between large corporate bankruptcy filings and traditional measures of economic health, such as GDP and unemployment rates. It also examines the relationship between bankruptcy filings and corporate bond issuances. The model presented shows that while there is no statistically significant relationship between the filings and the traditional measures of the economy, there does exist a relationship between the number of filings and the issuances of corporate bonds. The Article then uses this finding to explore a theory of collective knowledge—the idea that the aggregate information created by individuals for their own self-interest is more useful than a single source of knowledge—to explain the predictive power of bond issuances.

I. INTRODUCTION

The current state of the economy is frightening, and people of every socio-economic level are worried. In his weekly opinion column, Paul Krugman stated it "looks an awful lot like the beginning of a second

* Post-Graduate Research Fellow at and Class of 2009 graduate of Harvard Law School. I would like to thank Professors Elizabeth Warren and Lynn LoPucki, as well as the students in the Empirical Analysis of the Law class, for their guidance and comments throughout the writing process, and the Harvard-MIT Data Center for their statistical assistance. I would also like to thank Harvey Miller and Martin Bienenstock for their insightful comments on an earlier draft of this paper.
Great Depression." In January of 2009, 598,000 jobs were cut from the U.S. economy, and the unemployment rate rose to 7.6 percent—the highest it has been since 1992. The real gross domestic product ("GDP") decreased at an annual rate of 3.8 percent in the fourth quarter of 2008, and the United States has officially been in a recession since December of 2007. Even more headline-worthy has been the filing of bankruptcy by numerous large companies in 2008: Linens n' Things in May, Lehman Brothers in September, Circuit City in November, the Tribune Company in December—the list goes on. At the end of 2008, consulting group Bain & Co. predicted that there would be another 95 to 120 big companies that would fall in the next year.

It would seem that this level of large corporate bankruptcies would go hand in hand with high unemployment rates and declining GDP; however, this paper contends that this is not the case. This paper will show that there is no statistically significant relationship between either the GDP or unemployment rates and large corporate bankruptcy filings. There is, however, a statistically significant relationship between large corporate bankruptcy filings and corporate bond issues, both non-high-yield and high-yield. This Article explores the relationship between these filings and the corporate bond issues over the past twenty-seven years; it finds that high-yield bond issues are negatively correlated with filings, and non-high-yield bond issues are positively

correlated with filings. These findings present the opportunity to explore the application of a theory of collective knowledge—the idea that the aggregate information created by individuals working for their own self-interest is more useful than a single source of information. Here, people trying to maximize their wealth by investing in bonds can better predict the total number of bankruptcies in a given year than other traditional, economic indicators. This Article is divided into four parts. Part II discusses the background of this question. Part III explores the data set involved and statistical analysis used. Part IV details the theory offered to explain this relationship. Part V provides a conclusion.

II. BACKGROUND

While large corporate bankruptcies seem commonplace in today’s economic landscape, historically, the number in any given year is quite variable. Discovering ways to predict this variability is invaluable. Understanding these trends provides insight into why firms file for bankruptcy. Looking at the number of large bankruptcy filings over a span of close to thirty years, as presented in Figure 1, one notices

**Figure 1**
NUMBER OF LARGE BANKRUPTCIES FILED PER YEAR

10. This graph was created by the author of this paper in Stata from the raw data cited in the Data section below in Part III.A.
that there are periods where there are spikes in the filing rate. From 1998 to 2002, for example, the filing rate rose to almost 10 times what it had been previously, and then dropped back to its earlier levels. These spikes were the impetus for this research.

The literature regarding companies filing for bankruptcy is varied, but it mainly focuses on why a particular company files. There are two general methods for answering this question empirically: directly using accounting information of the company to predict bankruptcy, and using market-based information as a proxy for predicting bankruptcy. The most influential study using the first approach is found in Edward I. Altman's article entitled *Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy.* Altman's model, based on five accounting figures, produces a "z-score" that is used to predict the likelihood of bankruptcy. Despite its development forty years ago, the model is still used by both academics and practitioners.

The "z-score," with some modification, was later used by Altman to estimate credit ratings for emerging markets that were similar to U.S. bond ratings. The same model can also be used to assess the default likelihood of certain types of U.S. firms. This would suggest that there is a relationship between bond ratings and the likelihood a firm will file for bankruptcy.

A less common line of studies uses market information as proxies to help predict the likelihood that a single firm will file for bankruptcy. One example of this is illustrated in a book by Hillegeist, in which a model using Black-Scholes option pricing theory is shown to have more explanatory power in predicting bankruptcy than traditional accounting-based methods. Shumway's article presents another model that uses a hybrid of market-driven data and accounting information

11. See Figure 1 below.
12. Id.
15. Id. at 594. These five variables are working capital/total assets, retained earnings/total assets, earnings before interest and taxes/total assets, market value equity/book value of total debt, and sales/total assets. Id.
16. See id. at 606.
19. Id. at 139.
to predict bankruptcies for single firms.\textsuperscript{21} This line of studies suggests that market data can serve as a reasonable method of predicting bankruptcies.\textsuperscript{22}

While these models are useful in predicting the likelihood that an individual corporation files for bankruptcy, they do not address why many companies file for bankruptcy in the same year. The literature with regard to this macro-level question is surprisingly sparse. A news article suggested that bankruptcy booms follow declines in the sale of high-yield bonds.\textsuperscript{23} This Article presented a graph similar to Figure 2;\textsuperscript{24} however, the graph was based merely on speculation and no study was conducted.\textsuperscript{25} One can see that spikes in bankruptcy filings follow dips in high-yield bonds, and likewise, spikes in high-yield bonds tend

\begin{figure}
\centering
\includegraphics[width=\textwidth]{figure2.png}
\caption{Comparison of Large Business Bankruptcy Filings and High-Yield Bond Issues}
\end{figure}

\begin{itemize}
\item 22. See id.
\item 24. This graph was created by the author of this paper in Stata from the raw data cited in the Data section below in Part III.A.
\item 25. See Siew, \textit{supra} note 23.
\end{itemize}
to precede dips in bankruptcies. Bankruptcy expert Harvey Miller supports this theory by suggesting activity in the high-yield bonds can foreshadow bankruptcy booms.

Additionally, if, as suggested above, there is a connection between bond ratings and the likelihood a firm is going to go bankrupt, it would make sense that investors shifting away from high-yield bonds could indicate that the investors believe there will be an increase in corporate bankruptcies in the near future. Investors have access to a wide array of information, and if this information leads them to believe that there will be many companies filing for bankruptcies, they would no longer want to invest in those companies that have a higher probability of filing for bankruptcy—those with low bond ratings. Therefore, in times of trouble, high-yield bond markets should fall because investors are shifting money away from those firms that they think are likely to fail. Because of this, the bond markets should reflect the likelihood of bankruptcies. It is this relationship between bonds and bankruptcies, as well as the information investors signal in their actions, that this Article seeks to explore.

III. DATA AND MODEL

This Article tests whether aggregate information variables, such as bond issues, are better than traditional market indicators in predicting the number of large corporate bankruptcy filings in a given year. The model used in this Article looks at both high-yield and non-high-yield bond issues as examples of aggregate information variables. The variables contain information from independent actors making decisions for their own best interests. They use outside information from various sources to determine what choices they will make. This varied information is conveyed in the form of a market. Traditional economic indicators are represented by the GDP, the unemployment rate, and the discount rate. Both the data and model are described in more detail below.

26. See Figure 2 below.
27. See Harvey R. Miller, Chapter 11 in Transition—From Boom to Bust and Into the Future, 81 Am. Bankr. L.J. 375, 381 (2007). In discussing many different factors that make the current environment ripe for a bankruptcy boom, Miller notes increased activity in junk bond markets has helped create the bubble that he thinks will pop if there are significant changes in any of the factors, including the activity of junk bond markets. Id. at 378.
A. Data

The dependent variable, the bankruptcy filing information, comes from Prof. Lynn Lopucki’s Bankruptcy Research Database. It includes all cases of large, publicly traded companies who have filed for bankruptcy in the United States starting from October 1, 1979. This Article uses the data through 2007. The database considers a filing company “large” if the company reported assets of at least $100 million, measured in 1980 dollars, on the last Form 10-K the company filed with the SEC prior to filing for bankruptcy. A “case” includes all cases filed by members of the corporate group, provided that those cases are consolidated by the bankruptcy court for ease of administration. The year used for the model is the year in which the case was filed.

The bond information is from the SDC Platinum Database. The model uses two groups of corporate bonds—high-yield and non-high-yield. The definition for high-yield issues is the same as the definition provided by the high-yield filter in the SDC Platinum database. The filter defines high-yield issues as “the total value in millions of dollars of high-yield non-convertible U.S. public corporate debt and high-yield non-convertible 144 private placements issued in a given year.” Additionally, an issue must receive a high-yield rating from the ratings companies. The filter defines high-yield issues as “issues with an S&P rating equal to or less than BB+ and a Moody rating equal to or less than Ba1.” The filter defines non-high-yield corporate bonds as “the total value in millions of dollars of non-convertible U.S. public corporate debt and non-convertible 144 private placements not defined as high-yield issues issued in a given year.” The bond information used in this model spans from 1979 to 2007.

29. See id.
33. Id.
34. Id.
The GDP information comes from the Bureau of Economic Analysis. The information is annual data in billions of dollars, chained to year 2000 dollars. The unemployment rate information is from the Bureau of Labor Statistics. The model also uses the discount rate from December 31 of the given year from the Federal Reserve Bank of New York as a general indicator of interest rates at the time. Additionally, time is included as an independent variable.

B. Model

An OLS regression model is used to test the variables. The model uses the year-to-year differences in the variables to help alleviate concern that the observations lack independence from year to year. Moreover, the model uses robust errors to account for any heteroskedasticity among the variance. A visual inspection of the difference in filing frequency has shown that it is approximately normal. Furthermore, a Box-Ljung Q test showed that autocorrelation is not a concern of the model. While there is some correlation amongst the independent variables, there is no perfect collinearity, and the level of correlation is not enough to discount the model. Although there is the possibility of this model experiencing some omitted variable bias, such is the case with any model.

The results of this model can be seen in Table 1 below. The model has an r-squared value of .71. At the .01 level of significance, only high-yield bonds and non-high-yield bonds were significant. The discount rate was significant at the .05 level. No other variables, including the GDP and unemployment rate, were significant. The negative

38. The test was originally conducted with absolute values; however, a Box-Ljung Q test showed that there was strong autocorrelation in the model. The year-to-year differences were used to alleviate this concern. The original Q statistic was 27.95 and had a p value of 0.0056.
39. The test was also conducted without robust errors and achieved similar results. See tbl. A1 in the Appendix.
40. The Q statistic was 14.97 and had a p value of 0.18.
41. Independent variables can be correlated; they just cannot be perfectly correlated. See JEFFREY M. WOOLDRIDGE, INTRODUCTORY ECONOMETRICS, A MODERN APPROACH 90 (3d ed. 2006); see also tbl. A2 in the Appendix for the correlations amongst variables.
42. This table was created by the author of this paper in Stata from the raw data cited in the Data section above in Part III.A.
43. An initial test comparing each absolute variable solely against the filing frequency showed that each variable tested was statistically significant; however, these results do not take into
THE MARKET FOR FAILURE

Table 1

| Absolute change in high-yield bond issues | -0.0005391 |
| Absolute change in non high-yield bond issues | 0.0000645 |
| Absolute change in GDP | 0.0022253 |
| Absolute change in unemployment rate | -1.206807 |
| Absolute change in discount rate | -3.683799 |
| Time | -0.3779667 |
| Constant | 2.273348 |
| R^2 | .7111 |
| Observations | 27 |

Absolute value of t statistics in parentheses
* Significant at 5%; ** significant at 1%

coefficient for the high-yield bond figure confirms the notion, supra, that as issues of high-yield bonds decrease, the filing frequency for large corporate bankruptcies increases. Yet, there is a positive coefficient for non-high-yield bonds, indicating that as non-high-yield bond issues increase, filing frequency increases, as well. The difference in signs of the coefficients of the two types of bonds could possibly be explained by there being a flight to safety. That is, investors are pulling their funds out of high-risk ventures in times of trouble and putting them into safer options. According to this model, a $10 billion decrease in the year-to-year difference of high-yield bond issues, holding everything else constant, should increase the number of large companies that file for bankruptcy by five. Similarly, a $100 billion dollar increase in the year-to-year difference of non-high-yield bonds should increase the number of large companies that file for bankruptcy by six.44 While these changes in the value of bond issues seem high, it is

account the other variables, so there is great omitted variable bias, as well as the possibility of conflating variables. This does, though, give a reasonable basis for including these variables in the model.

44. While the coefficients of the statistically significant variables seem vastly different from each other, this is due to the fact that the base numbers for the discount rate are single percentages, while the bond data many is magnitudes greater. These figures are meant to show that reasonable changes in bond activity will have an effect on filing rates and will not be dwarfed by changes in the discount rate.
important to keep in mind that, in 2007, the value of high-yield bond issues was nearly $100 billion and the value of non-high-yield bond issues was over $2 trillion.

Figure 3 below shows a comparison of the actual differences in filing rates and those predicted by this model. Figure 3 shows that this model does a fairly good job at predicting the differences. Using this information, this Article compares the projected filing frequency based on this model with the actual filing frequency, the results of which can be seen in Figure 4 below.

While the statistical model answers the question of what is correlated with bankruptcies, it also brings up the question of why the GDP and the unemployment rate are not correlated with bankruptcy. Long-time corporate bankruptcy practitioner and lecturer, Martin Bienenstock, said the following as to why businesses file for bankruptcy:

Most hedge funds concentrating in distressed debt will tell you that their investors invest with them because they are uncorrelated with the economy. This has always been consistent with my unscientific observations. Large companies usually don’t fail because sales fall

**Figure 3**

**ABSOLUTE YEARLY CHANGE IN LARGE BANKRUPTCY FILINGS**
**ACTUAL VS. PREDICTED**

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45. This graph was created by the author of this paper in Stata from the raw data cited in the Data section above in Part III.A.

46. See Figure 3 below.

47. This graph was created by the author of this paper in Stata from the raw data cited in the Data section above in Part III.A.
5% in recessions. Rather, the two greatest causes of bankruptcy have always seemed to me to be: (a) unplanned for change (e.g., deregulating airline ticket prices in 1980, OPEC losing control of the price of oil, deflation, technological improvements making fiber optic cable capable of carrying more data than anyone thought, reductions in Medicare reimbursement rates, etc.) and (b) illiquidity in the high yield market. 48

The difference may lie in a key difference between both the GDP and the unemployment rate and bond markets. Both the GDP and the unemployment rate only measure the health of the economy whereas bond markets take into account other sources of information.

The economy is only one of many factors that determine the health of a business. Other factors include consumer demand, changes in technology, and management practices. These other factors may have no relationship to the general economy, but they are integral to the health of the business. It would make sense then, that the GDP and the unemployment rate, which measure the health of the economy, are not the best predictors of bankruptcy. They are too narrow. Bond markets, on the other hand, take all of these factors into account because investors use knowledge of these factors in making their deci-

sions as to where to invest. For example, in a time of great innovation, the economy may be doing very well, which would be reflected as a high GDP and low unemployment rate. However, the new technology would make many old technologies obsolete, which would cause many companies to go bankrupt. While the GDP and the unemployment rate would not reflect the loss of these companies, one would expect the bond issues to reflect this to an extent, since an investor’s decision as to where to invest would reflect all of his or her available knowledge—that is, if investors are not putting their money into high-yield bonds, the number of issues should decrease.  

IV. Theory

The model tested in this paper is great for generating numbers and telling us which numbers are relevant, but it is not effective in trying to figure out why the results are the way they are. Why is it that bond issues correlate strongly with corporate bankruptcies while the GDP and the unemployment rate—two factors that might reasonably be predicted to correlate with bankruptcies—do not? The answer may lie in a collective knowledge theory, sometimes known as the “wisdom of crowds” or “smart mobs.”

Many people use the power of collective knowledge everyday, often without thinking about it. Wikipedia, the online encyclopedia, is likely the most universal example. Hosting over 3,061,587 English-language articles, Wikipedia is accessed by over 67 million people per month. Articles are written and edited by anyone, yet Wikipedia still manages to have the same level of accuracy as Encyclopedia Britannica. Elsewhere online, people use ranking systems,
which aggregate the opinions of numerous individuals to decide which blender to purchase from Amazon or which restaurant to patron from Yelp. Collective knowledge permeates people’s everyday lives.

This theory of information is not, however, limited to finding the best restaurants in the area or figuring out an obscure fact. Many papers and books have been published in the past few years discussing the phenomena. One such example is a paper written by Beth Simone Noveck that discusses applying the power of collective knowledge to the patent review system. In 2007, the United States Patent and Trademark Office (“USPTO”) launched a pilot program to have patent applications reviewed in part by members of the public. Anyone was allowed to review the applications and submit comments. The top findings for each application were then forwarded to the USPTO. The goal was to connect “the public and its deep and wide expertise to government decision-making,” with the end result being stronger legitimate patents and the elimination of illegitimate patents. The pilot program was considered to be successful, and it was extended for another year.

Many of these collective knowledge theories are based on the Condorcet Jury Theorem. The theorem says that, given two alternatives—one of which is correct—a group of individuals choosing between the two alternatives will more likely than not choose the correct alternative. This will occur because an average member of the group has a more likely than not probability of guessing the correct answer, and as the number of individuals increases, the likelihood of the group being correct approaches certainty. It has been suggested that the theorem holds true even when there are more than two

56. See e.g. Cass R. Sunstein, Infotopia, How Many Minds Produce Knowledge (2d ed. 2008); see also Surowiecki, supra note 33; Rheingold, supra note 33.
59. See id.
61. Id. at 4.
63. Adrian Vermeule, Many-Minds Arguments in Legal Theory, 1 J. L. Analysis 1, 4 (2009).
64. Id.
65. Id. at 5.
choices. Put more simply, when faced with a question, a large group of individuals, having a mean probability of guessing the right answer greater than random, will correctly decide the question with increasing certainty as the size of the group increases.

Additionally, these knowledge aggregation models can also find much of their basis in the work of Friedrich Hayek. In fact, the founder of Wikipedia credited Hayek as being his muse in creating Wikipedia. Hayek believed that in a system where knowledge of a relevant subject is spread throughout the population, markets effectively aggregate the information and communicate it to everyone. The invisible hand of the market knows more about a given situation than any single person knows.

As applied to the bond markets, the theory is fairly straightforward. There is a group of individuals—mainly professional investors, but not necessarily so—who have access to information about the market. This information is independently obtained by each actor in the group and differs from the information other individuals have in the group, although some of the information may overlap. Using his or her own information, each individual acts in accord with his or her own best interest, changing the overall demand for different types of bonds. Responding to this change in demand, companies change their issues to match it. That is, when there is a high demand for high-yield bonds, there will be a greater supply for high-yield bonds, and vice versa. Because the individuals are using their information to make decisions about what bonds to purchase, this information, as well as the information of other individuals, is reflected in the bond markets. Just as a Wikipedia article takes bits of knowledge from editors around the world to present a clear picture of the facts, the bond market aggregates investors' bits of knowledge about the health of the corporate economy.

By understanding the way the bond market aggregates the varied information of its participants, it becomes clear as to why the regression model generated such results. The variables that reflect the aggregate information of investors, the bond markets, are statistically significant, while those that just reflect general economic information, the GDP and the unemployment rate, are not.

69. See Friedrich Hayek, supra note 48, at 526.
V. Conclusion

While there is extensive literature regarding the prediction of bankruptcy in individual firms, there are few efforts to predict the total number of firms filing for bankruptcy in a given year. This paper explores the idea that there is a relationship between high-yield bonds and large business bankruptcies, as was suggested by some of the previous literature. The data reported here shows that there is indeed a statistically significant relationship between bond issues and bankruptcy filings, while traditional measures of economic health, the GDP and the unemployment rate, are not significant. These results are supported by a theory of collective knowledge in that the bond markets serve as a depository of knowledge of the individual investors. By aggregating the decisions of investors, the markets are able to reflect the collective knowledge that is held by these individuals and to serve as a better indicator of the number of corporate bankruptcies than standard economic indicators that are not based on the collective knowledge of individuals.

70. See Section II above.
APPENDIX

**Table A1**

<table>
<thead>
<tr>
<th>Absolute Change in Filing Frequency</th>
<th>Absolute Change in high-yield bond issues</th>
<th>Absolute Change in non high-yield bond issues</th>
<th>Absolute change in GDP</th>
<th>Absolute change in unemployment rate</th>
<th>Absolute change in discount rate</th>
<th>Time</th>
<th>Constant</th>
<th>R²</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>-0.0005391</td>
<td>0.0000645</td>
<td>0.0022253</td>
<td>-1.206807</td>
<td>-3.683799</td>
<td>-0.3779667</td>
<td>2.273348</td>
<td>2.273348</td>
<td>0.7111</td>
</tr>
<tr>
<td></td>
<td>(5.84)**</td>
<td>(4.67)**</td>
<td>(0.08)</td>
<td>(0.33)</td>
<td>(2.09)*</td>
<td>(1.52)</td>
<td>(0.34)</td>
<td>2.273348</td>
<td>.7111</td>
</tr>
</tbody>
</table>

Absolute value of t statistics in parentheses

* Significant at 5%; ** significant at 1%

**Table A2**

**Correlations Amongst Variables in the Model**

<table>
<thead>
<tr>
<th>Frequency</th>
<th>GDP</th>
<th>Unemployment</th>
<th>Discount rate</th>
<th>High-yield Bond</th>
<th>Non high yield bond</th>
<th>Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Frequency</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>GDP</td>
<td>-0.1868</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment</td>
<td>0.1349</td>
<td>-0.7917</td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Discount rate</td>
<td>-0.4076</td>
<td>0.7205</td>
<td>-0.5968</td>
<td>1.0000</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High-yield bond</td>
<td>-0.2218</td>
<td>-0.1374</td>
<td>0.0690</td>
<td>-0.3718</td>
<td>1.0000</td>
<td></td>
</tr>
<tr>
<td>Non high-yield bond</td>
<td>0.2811</td>
<td>-0.0112</td>
<td>0.0279</td>
<td>-0.3802</td>
<td>0.7360</td>
<td>1.0000</td>
</tr>
<tr>
<td>Time</td>
<td>-0.1929</td>
<td>0.3693</td>
<td>-0.0409</td>
<td>0.2821</td>
<td>0.0215</td>
<td>0.1827</td>
</tr>
</tbody>
</table>

Variables reflect year to differences.

71. This table was created by the author of this paper in Stata from the raw data cited in the Data section above in Part III.A.

72. This table was also created by the author of this paper in Stata from the raw data cited in the Data section above in Part III.A.