XVI

Volume XVI, Number 1, May 2013

Journal of Applied Economics

Jin Zhang
David A. Bessler
David J. Leatham

Aggregate business failures and macroeconomic conditions: A VAR look at the U.S. between 1980 and 2004

UCEMA

Edited by the Universidad del CEMA
Print ISSN 1514-0326
Online ISSN 1667-6726

Journal of Applied Economics. Vol XVI, No. 1 (May 2013), 179-202

AGGREGATE BUSINESS FAILURES AND MACROECONOMIC CONDITIONS: A VAR LOOK AT THE U.S. BETWEEN 1980 AND 2004

Jin Zhang*
Southwestern University of Finance and Economics

David A. Bessler and David J. Leatham
Texas A&M University

Submitted April 2010; accepted May 2012

In this paper, we study the U.S. aggregate business failures during 1980- 2004 in relation to four macroeconomic variables: aggregate corporate profits, the producer price index, the interest rate, and stock market performance. We argue that aggregate business failures should not be treated as a passive variable, as usually done in previous studies, and we allow its possible causal effect on other macroeconomic variables through a Structural Vector Autoregression model that builds on Directed Acyclic Graphs. Granger type causality and innovation accounting results both show that while subject to the influence of interest rates, aggregate business failures are quite exogenous in comparison to the other three variables. The implications of these findings are discussed as well.

JEL classification codes: C32, E51, G33
Key words: business failures, macroeconomic conditions, directed acyclic graphs, vector autoregression

---

* Jin Zhang (corresponding author): Research Institute of Economics and Management, Southwestern University of Finance and Economics, Chengdu, Sichuan 610074, China; e-mail: jin.zhang@swufe.edu.cn. David A. Bessler: Department of Agricultural Economics, Texas A&M University, Colleges Station, TX 77843; e-mail: d-bessler@tamu.edu. David J. Leatham: Department of Agricultural Economics, Texas A&M University, College Station, TX 77843; e-mail: d-leatham@tamu.edu. We would like to thank one co-editor and two anonymous referees for the many helpful comments and suggestions. All errors are ours.

I. Introduction

The issue of business failures (or bankruptcies, interchangeably) has drawn extensive attention over the past half century, which is not surprising given the huge costs usually associated with business failures. The vast majority of the literature on this issue deal with business failures at the micro level, especially the prediction of individual business failures based on firm-specific information. At the macro level, there is a line of research that addresses the overall business failures in an economy and its relationship with other macroeconomic conditions, but it is far less extensive than those at the micro level, both theoretically and empirically.

The macro line of research on business failures was started by Altman (1971, 1983). In his studies, Altman first identified a set of macro variables that are likely to cause the failure of individual firms, including economic growth, credit or money market conditions, stock market activity, and business population characteristics. He then tested the possible causal effects on aggregate business failures in a distributed-lag regression model based on U.S. data. Since then, others have updated the research along this line, including Rose, Andrews, and Giroux (1982), Hudson (1986), Wadhwani (1986), Melicher and Hearth (1988), Platt and Platt (1994), and more recently, Liu (2004, 2009). Roughly speaking, these empirical studies have reached a consensus on the effects of certain variables on business failures, notably, corporate profits and interest rates. However, they have conflicting opinions on other variables, especially the price level and stock market performance. The potential reasons for differing results range from different samples (different periods in different countries, hence potentially different economic structures and institutional backgrounds) to the conceptual frameworks, and methodology adopted.

In this study, we re-examine the relationship between business failures and macroeconomic conditions for the case of the United States. As a first motivation of this study, we examine the post-1980 period to provide a more recent and relevant coverage. Unlike other economic events or variables, bankruptcy, either personal or business, is also a legal phenomenon, governed directly by corresponding legal procedures. Aggregate business failures are inevitably subject to the influence of changes in legal systems (see Liu 2004 for the empirical evidence in the case of the U.K.). Since the early 20th century, the U.S. bankruptcy legal system was defined first by the Bankruptcy Act of 1938. Then the Bankruptcy Reform Act of 1978 came into effect and changed the legal environment of bankruptcy

substantially. Among the limited studies on the U.S. case, however, no paper has effectively covered the issue for the period since 1980. To reflect a more relevant reality, we choose to study the relationship between business failures and macro conditions for the period from 1980 to 2004. On one end, we choose 1980 as the beginning because it is the first year following the passage of the Bankruptcy reform Act of 1978 on October 1, 1979. On the other end, we choose not to extend the coverage beyond 2004, to avoid the complication (structural change) that may be caused by the more restrictive bankruptcy code (the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005) and the turbulent financial crisis that immediately followed.

Second, as a further motivation, we feel that the approach usually followed in the existing literature emphasizes the one-way causality from other variables to aggregate business failures, but the reverse causality from aggregate business failures is largely ignored, which leaves the whole picture incomplete. Since Altman (1971), studies in this context usually begin with an intention to find what determines business failures, and macro variables are identified as potential determinants if they are believed to influence the failure of individual firms. The issue is, even if the causality from macro variables to individual business failures is true, it is questionable whether we can apply this relationship to the macro level, i.e., to aggregate business failures. By using the macro conditions thus identified as the right-hand-side variables and estimating their effects on aggregate business failures with the usual regression methods, the potential exogeneity of aggregate business failures or its causal flows to other variables is a priori ruled out. Conceptually, aggregate business failure may not be such a passive variable; instead, it may play a proactive role in the overall economy (Bernanke 1981). Therefore, a more flexible framework should be employed to allow for this possibility.

The more flexible framework we employ in this study is Vector Autoregression (VAR) that builds on a data-determined identification from Directed Acyclic Graphs (DAG). VAR (Sims 1980) is an econometric framework flexible enough in the sense that all variables considered are treated as potentially endogenous. Only minimal assumption on structure is needed, which makes VAR a good candidate for the issue at hand, given that the causal structures among variables are unclear. To date, VAR has not been used to study this issue, except in Liu (2009) wherein the case of the U.K. was studied in the setting of Vector Error Correction (VEC). For VAR to be useful for policy analysis, the underlying structure has to be identified, and the identification methods of Choleski and Structural VAR (SVAR;

Sims 1986; Bernanke 1986) have been widely used. Rather than following these two approaches, we rely on DAG and the inductive causality algorithms to provide a "data-driven" causal structure for identification. With an origin in artificial intelligence and computer science, this "data-driven" approach does not make a prior assumption on causal structure, but instead produces the structure from data. Therefore, this approach may produce a more objective analysis than those based on Choleski decomposition or a structural model based on subjective grounds (Swanson and Granger 1997). In the remainder of this paper, Section II introduces the conceptual framework and data. A description of econometric methods follows in Section III. Section IV presents the empirical implementation, as well as the results and discussions. Section V concludes.

II. Conceptual framework and data

We first identify a variable to represent the business failure activity at the macro level. Primarily two measures have been used in the literature to describe aggregate business failures, i.e., the business failure rate in percentage (e.g., Altman 1983), and the business failures in numbers (e.g., Melicher and Hearth 1988). Compared with the latter, the business failure rate gives clearly an unconditional probability of failures for firms in the economy; however, for the U.S., the influential Dun & Bradstreet business failure rate used in previous studies was discontinued after 1997. Yet, at the same time, as business failures (and births, too) account for a very small portion of total active firms (no more than 2 percent per annum, even in the worst years), the business failures in numbers mimics closely the time series pattern of the business failures in percentage (Chava and Jarrow 2004). Given the purposes of this study, where our interest is essentially focused on the dynamic pattern of business failure activity and its relationship with other variables, we choose the business failures in numbers to enable coverage up to 2004.

We then identify relevant macroeconomic variables by examining the effects of a list of macro variables on a firm's propensity to fail. Such an examination suggests that particular macroeconomic variables potentially influence business failures, including economic growth, monetary conditions, inflation, and stock market performance. This approach, which identifies related macro variables, is essentially the same as that used in Altman (1983), Liu (2004, 2009), and Platt

and Platt (1994), among others.[1] Before we deviate from existing studies in the following econometric analysis, the content of such an examination for macro variable identification is laid out in the following four paragraphs.

First, economic growth is considered important because it may have a direct influence on a firm's sales and earnings. Sales and earnings are two direct and important measures of a firm's current performance and provide the cash flow critical to the firm's continued survival. An overall economic index, such as gross national product or aggregate corporate profits, may be used for this condition (Altman 1983). We choose aggregate corporate profits because they measure the business health of firms directly. This variable is used extensively in the literature and has usually been found significant and negatively associated with business failures.

Money, or credit availability and its cost, is another factor believed to have a direct impact on the survival of a marginal firm. "Regardless of how poorly a firm is performing, it seldom is motivated to declare bankruptcy as long as liquidity is sufficient or credit is available" (Altman 1983). It is then reasonable to expect that the aggregate business failures will increase as credit conditions become tighter. Following the literature, we choose interest rates to capture monetary conditions.

The effect of inflation on aggregate business failures is less clear. Inflation is generally an important indicator of the overall economy, and its effect on business failures may be twofold. On one hand, as Altman (1983) postulated, inflation, especially unanticipated price increases, "tend to be inversely correlated with failure rates," because leveraged firms can repay their debts with "cheaper" money, and also because inflation may cause reduced competitiveness. On the other hand, inflation may result in more failures as it makes the earnings of a firm more volatile and harms its capability to repay its debt (Wadhwani 1986). Some evidence (Wadhwani 1986; Liu 2004, 2009) suggests that inflation leads to more business bankruptcies. Thus, inflation is included as a third variable that may affect aggregate business failures.

Stock market performance is the fourth factor that we consider. The stock price of a firm is usually believed to reflect the firm's economic value, whereas

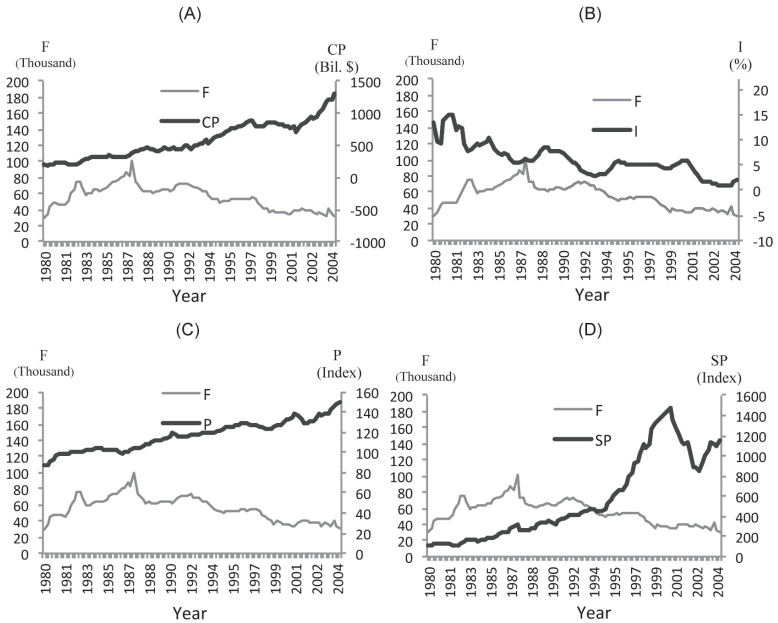
[1] Although these studies all identify macro variables by starting with an examination of individual firm failure, the macroeconomic variables selected in each study vary. The variables chosen in our study are closer to those in Altman (1983) and Liu (2004, 2009). Compared with these two studies, we place less emphasis on the composition of business failures and do not include new firm formation variables. In the meantime, we include inflation (compared with Altman 1983) and stock market performance (compared with Liu 2004, 2009).

stock price indices, such as the S&P 500 stock price index, indicate the overall expectation about the future of the whole economy. Altman (1983) argued that stock market performance affects firm failures because a potential failing firm will not go bankrupt "if the future appears hopeful," as indicated by investor expectations or stock market performance. For the same reason, a falling stock price, indicative of a firm's falling economic values, may also increase a firm's propensity to fail. At the aggregate level, both stock market performance and aggregate business failures are labeled as leading indicators, but which of the two causes the other is another issue. Among existing studies (Rose, Andrews, and Giroux 1981; Altman 1983; Melicher and Hearth 1988), the effect of stock market performance, as represented by the S&P 500 stock price index, on business failures has been found significant, with inconsistency regarding the sign. The possible causality in the reverse direction, i.e., the effect of business failures on stock market performance, should also be allowed, and we let data tell us if this possible effect is true.

Five U.S. quarterly data series, measured over 1980 to 2004 with a total of 100 observations, are used to represent the five variables discussed above.[2] The number of total business bankruptcies (F) is used to measure the aggregate business failures in the U.S. The other four variables, i.e., corporate profits (CP), the 3-month T-Bill yield (I), the producer price index of all commodities (P), and the S&P500 stock price index (SP), are used to reflect economic growth, money supply and credit conditions, the price level, and investor expectations, respectively. The five data series have been obtained from the following sources: the number of total business bankruptcies from the Office of U.S. District Courts, corporate profits from the Bureau of Economic Analysis, the 3-month T-bill yield from the Federal Reserve Bank, the producer price index of all commodities from the Bureau of Labor Statistics, and the S&P 500 stock price index from Standard & Poor's. A graphical presentation of all five variables is given in Figure 1, with business failures presented against each of the other four macroeconomic variables. The ordinary correlations between aggregate business failures and corporate profits, the T-Bill yield, the producer price index, and the S&P 500 stock price index are -0.697, 0.269, -0.637, and -0.736, respectively, which are all significant at the 1 percent level. These correlations are largely consistent with the relationships hypothesized above. However, we are unable to say much about the causality among the five variables without further analysis.

[2] The three-month T-Bill yield and producer price index of all commodities were originally monthly data and were transformed into quarterly data by taking the average of the monthly figures.

Figure 1. Movements of aggregate business failures against four macro variables



Note: In the four small graphs, the vertical axis on the left hand side corresponds to aggregate business bankruptcies (F), while the vertical axis on the right hand side is used for corporate profits (CP), the interest rate (I), the producer price index (P), and the S&P 500 stock price index (SP), respectively. In terms of units, F is in number of thousands, CP in billions of dollars, I in percent, P and SP in index as usually defined. To distinguish the line for F from those for other four variables, the lines for the other four variables are shown in bold.

As a preliminary analysis, the five data series are each tested for stationarity using augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. The null hypothesis of both tests is that the series tested is nonstationary. As reported in Table 1, by the ADF test, nonstationarity cannot be rejected at the 5 percent level for both the case of trend and the case of no trend for all five series. The PP test also finds the data series to be nonstationary. Further tests on the first differences of these data suggest them to be stationary. Therefore, all five series are treated as I(1) in the following analysis.

Table 1. ADF and PP tests for nonstationarity

Series	ADF		PP	
	Without trend	With trend	Without trend	With trend
Variables in level				
F	-0.98	-3.46	-1.51	-3.44
CP	1.36	-1.37	1.39	-1.61
I	-1.48	-2.97	-2.15	-3.05
P	-0.10	-2.93	-0.32	-2.76
SP	-0.47	-2.01	-0.54	-2.03
Variables in first difference				
F	-11.31	-11.53	-11.22	-11.43
CP	-10.26	-10.48	-10.35	-10.52
I	-8.73	-8.67	-8.76	-8.70
P	-6.15	-6.14	-6.16	-6.13
SP	-6.07	-6.05	-6.17	-6.15

Note: F stands for aggregate business bankruptcies, CP for corporate profits, I for the interest rate, P for the producer price index, and SP for the S&P 500 stock price index. ADF is a unit root test developed by Dickey and Fuller. PP is a unit root test developed by Phillips and Perron. Critical values for the ADF test at 5 percent level with constant only and with constant and trend are -2.89 and -3.46, respectively. Critical values for the PP test at 5 percent level with constant only and with constant and trend are -2.891 and – 3.456, respectively. For both tests, nonstationarity is rejected when calculated values are less than critical values.

III. Methodology

Given the data being I(1), we consider a cointegrated VAR that allows for possible cointegration among the five variables. Let Y_t denote the vector that contains the five studied variables. Assuming for now the existence of cointegration, the system of five variables can then be described below by a VEC Model (VECM), as developed by Johansen (1991):

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \mu + \Psi Z_t + e_t \quad , \tag{1}$$

where $t = 1,...,T$, Δ is the difference operator ($\Delta Y_t = Y_t - Y_{t-1}$), Π is a $N \times N$ matrix ($N = 5$ in this case) of coefficients for long run relationship, k is the lag length for the VAR of undifferenced variables, Γ_i is a $N \times N$ matrix of coefficients for the i_{th} lagged period, μ is a $N \times 1$ vector of constant, Ψ is the coefficient matrix associated with exogenous variables Z_t , and e_t is a $N \times 1$ vector of residuals.

From the above data generation process, we can obtain the interrelationship between variables from different perspectives. First, based directly on the estimated VECM in equation (1), the short-run Granger dynamics can be read from Γ_i; also available from equation (1) is the long-run relationship among the possible cointegrated variables from Π. Further, from e_t or its covariance matrix, the contemporaneous causal structure can be derived via DAG. Finally, based on contemporaneous causality as the identification condition for SVARs, the short-run relationship can be summarized through the innovation accounting techniques, i.e., impulse response function (IRF) and forecast error variance decomposition (FEVD). Although VECM models the variables in their first differences, after transformation, the relationship given by innovation accounting is actually in terms of the original level variables, as shown below:

$$Y_t = (I + \Pi + \Gamma_1)Y_{t-1} - \sum_{i=1}^{k-2}(\Gamma_i - \Gamma_{i+1})Y_{t-i-1} - \Gamma_{k-1}Y_{t-k} + \mu + \Psi Z_t + e_t \quad , \tag{2}$$

where I is an identity matrix of $N \times N$ ($N = 5$ in this case). In the remainder of this section, we explain particularly the DAG-based contemporaneous causal structure for VAR identification.

A. VAR identification based on contemporaneous causal structure

For innovation accounting analysis to reveal the causal relationships among the variables in the VAR system, identifying structural shocks from observed residuals is important. The identification approach suggested by Sims (1980) relies on the Choleski decomposition of contemporaneous correlation (covariance matrix) of residuals. However, the recursive contemporaneous causal ordering implied in Choleski decomposition is simply too restrictive, oftentimes not true, and thus misleading. Therefore, SVAR has been suggested as a decomposition that can incorporate a more flexible prior causal structure (Sims 1986, Bernanke 1986). Early proponents of the SVAR used a prior theory to suggest a structural decomposition. Nevertheless, the problem is not solved if a causal structure is not available from theory, or even if we have one but it is not objective (Swanson and Granger 1997).

More recently, a data-determined SVAR framework has been advocated by Swanson and Granger (1997) and Demiralp and Hoover (2003), and applied by Awokuse and Bessler (2003), and Bessler and Yang (2003), among others. In this framework, DAG, a method of causal inference, is used to provide the contemporaneous causal order required in a SVAR. The issue we study in this

paper represents exactly a situation where no predetermined (theoretical) contemporaneous causal structure can be used. A data-driven approach that does not assume a priori knowledge of causality is justified. We discuss such a data-driven DAG method below.

B. Directed acyclic graphs

Directed graph, developed in computer science, represents a graphical way to describe the causal flows among a set of variables. A directed graph can formally be described as a triple (V, M, E), where V is a non-empty set of vertices standing for variables studied, e.g., a set of five vertices for the five variables in this study; M is a non-empty set of symbols (usually arrowhead or empty) attached to the ends of undirected edges; and E is a set of ordered pairs defining the combination of vertex and symbol for the ends of undirected edges (Spirtes, Glymour, and Scheines 2000). Consider two variables A and B among a set of variables V. Probably the most interesting information out of a directed graph is a directed edge, such as $A \rightarrow B$, indicating that variable A causes variable B. However, a directed edge is not the only possibility. Other types of edges, bi-directed ($A \leftrightarrow B$) and undirected ($A - B$), may also appear in a directed graph, suggesting mutual causality or lack of information to direct causality. Among directed graphs, DAG, a graph type that contains no cyclic paths of causal flows, is the type suitable for this study.

In a statistical sense, DAGs are designs to express conditional independence. As a graphical way to characterize conditional independence, the notion of D-separation (dependence separation) was proposed by Pearl (1986), and it has been incorporated into the algorithms for building directed graphs, especially the PC algorithm. Details on this basic PC algorithm and its derivatives can be found in Spirtes, Glymour, and Scheines (2000). Very briefly, from an operational perspective, to produce a DAG, the algorithm begins with a complete undirected graph, wherein an undirected edge exists between every two variables (contained in V). Then, the undirected edges between variables are removed sequentially in case of zero correlation or partial correlation (conditional correlation), as tested using Fisher's z. Finally, the remaining undirected edges are assigned a direction (directed) using the concept of sepset.[3]

[3] Consider for concreteness a set of three variables connected as $X - Y - Z$, wherein the edge between X and Z has already been removed. The sepset means the conditioning variable(s) for the removed edge between X and Z. To use sepset, if Y is not one of the variables in X and Z's sepset, then the direction can be assigned as $X \rightarrow Y \leftarrow Z$.

Based on the Monte Carlo simulations of the PC algorithm (Spirtes, Glymour, and Scheines 2000; Demiralp and Hoover 2003), for sample sizes of 100, the PC algorithm may exclude (or include) edges incorrectly and/or probably more likely assign the directions of edges incorrectly. Spirtes, Glymour, and Scheines (2000, p. 116) pointed out, "In order for the methods to converge to correct decisions with probability 1, the significance level used in making decisions should decrease as the sample size increases and the use of higher significance levels (e.g., 0.2 at sample size less than 100, and 0.1 at sample size between 100 and 300) may improve performance at small sample sizes." Based on their suggestions, the DAG results at various significance levels, from 0.1 to higher, are explored in the present study.

IV. Results and discussions

Having previously established in Section II that the five variables used in this study are I(1), we model them in VECM and interpret the estimated model in terms of short-run and long-run (Granger type) causality. DAG will then be applied to use the VECM residual information to obtain the contemporaneous causal structure. After obtaining this causal structure, the structural VECM underlying the reduced VECM is estimated or identified, and further, transformed into the usual VAR model in level variables. Finally, the IRF and FEVD analyses are carried out to reveal the interactions among the original level variables instead of their first differences.

To build this VECM, the optimal lag length for a VAR of the five variables in their first differences is obtained by minimizing Schwarz and Akaike loss criteria. Specifically, the Schwarz and Akaike loss criteria give the optimal lag of 1 and 3, respectively. A lag of 1 would be preferable based on the parsimony principle. In addition, subsequent LM tests of the VECM model based on the lag of 1 suggests no presence of autocorrelation in the residuals. Thus, the lag of 1 is chosen. We then verify the existence of cointegration in the variables using the trace test of Johansen. As shown by the results reported in Table 2, three cointegration vectors with a linear trend exist among the five variables.

Table 2. Trace test statistics for the studied variables

r	Without linear trend			With linear trend		
	T	C(5%)	C(10%)	T	C(5%)	C(10%)
=0	124.21	75.74	71.66	100.68	68.68	64.74
<=1	73.47	53.42	49.92	53.64	47.21	43.84
<=2	40.51	34.80	31.88	32.25	29.38	26.70
<=3	21.03	19.99	17.79	13.63	15.34	13.31
<=4	5.90	9.13	7.50	1.21	3.84	2.71

Note: The trace test indicates the number of cointegration vectors (r) for cases with and without constant. The critical values (C) at the 5 and 10 percent levels are as given in Hansen and Juselius (1995). To determine the number of cointegration vectors, we start with the top row and move from the left column of "with constant" to the right column of "without constant." This process continues to the next row until we meet the first "fail to reject" case, i.e., when the trace test statistic (T) is less than the critical value (C).

The VECM model with three cointegration vectors and trend in the series are estimated (with t-statistic in parenthesis), as shown in the equation:

$$\begin{bmatrix} \Delta F_t \\ \Delta CP_t \\ \Delta I_t \\ \Delta P_t \\ \Delta SP_t \end{bmatrix} = \begin{bmatrix} 6885.59 \\ (0.66) \\ 293.13 \\ (4.46) \\ 7.59 \\ (4.52) \\ 9.51 \\ (3.27) \\ 125.16 \\ (1.50) \end{bmatrix} + \begin{bmatrix} -0.22 & -11.76 & -1033.48 & -227.44 & -4.25 \\ (-2.17) & (-0.70) & (-1.87) & (-0.71) & (-0.37) \\ 0.001 & -0.28 & 7.05 & -1.15 & -0.34 \\ (1.83) & (-2.60) & (2.02) & (-0.56) & (-0.47) \\ 0.00 & -0.00 & 0.20 & 0.13 & 0.01 \\ (0.58) & (-0.34) & (-2.29) & (2.44) & (3.09) \\ 0.00 & 0.01 & 0.19 & 0.39 & 0.01 \\ (1.20) & (1.56) & (1.25) & (4.33) & (2.15) \\ 0.00 & -0.30 & 0.39 & -4.49 & 0.94 \\ (1.36) & (-2.26) & (0.09) & (-1.74) & (3.20) \end{bmatrix} \cdot \begin{bmatrix} \Delta F_{t-1} \\ \Delta CP_{t-1} \\ \Delta I_{t-1} \\ \Delta P_{t-1} \\ \Delta SP_{t-1} \end{bmatrix}$$

$$+ \begin{bmatrix} -0.10 & 1.78 & 434.60 & -35.90 & -1.61 \\ (-1.75) & (0.25) & (1.47) & (-0.54) & (-0.81) \\ -0.00 & 0.02 & -7.98 & -1.46 & -0.03 \\ (-2.84) & (0.50) & (-4.26) & (-3.49) & (-2.51) \\ -0.00 & -0.00 & -0.22 & -0.03 & -0.00 \\ (-4.18) & (-1.11) & (-4.70) & (-2.70) & (-1.51) \\ -0.00 & 0.00 & -0.17 & -0.04 & -0.00 \\ (-3.03) & (0.16) & (-2.08) & (-2.41) & (-1.88) \\ 0.00 & 0.26 & 1.84 & -2.08 & -0.07 \\ (0.54) & (4.49) & (0.78) & (-3.93) & (-4.33) \end{bmatrix} \cdot \begin{bmatrix} F_{t-1} \\ CP_{t-1} \\ I_{t-1} \\ P_{t-1} \\ SP_{t-1} \end{bmatrix} . \quad (3)$$

A. Short-run and long-run Granger causality

In equation (3), the first term on the right hand side represents the constant, and the second term represents the short-run dynamics. From the second term, we see that the change in business failures is primarily caused by the change in business failures from the previous period. The changes in other variables do not have significant effects on changes in business failures, except that the effect of the interest rate is marginally significant. From another perspective, we also can see that the change in business failures has a marginally significant effect on corporate profits, but no significant effect on the other three variables.

The third term on the right hand side of equation (3) represents the long-run relationship among the five variables. More specifically, this term can be decomposed as $\Pi = \alpha\beta'$, where α is a N x r matrix and β is a r x N matrix, given that we have N (=5) variables and r (=3) cointegration vectors. a is usually interpreted as a loading matrix representing the speed of adjustment to deviations from the long-run equilibrium among the cointegrated variables, where β as contains the coefficients in the r cointegrating vectors. For variable p $(p = 1, \cdots, N)$ on the left hand side, its overall response to the long-run disequilibrium depends on the sum of its responses to all q $(q = 1, \cdots, 3)$ individual disequilibria via its loading coefficient α_{pq}. For example, the overall response of ΔF_t to the long-run disequilibrium may be written more specifically as $\alpha_{11} \cdot disequilibrium_1 + \alpha_{12} \cdot disequilibrium_2 + \alpha_{13} \cdot disequilibrium_3$, where $disequilibrium_q$ represents the amount of deviation from each of the three cointegration relationships. Each cointegration relationship is defined as $\beta_{q1} \cdot F_{t-1} + \beta_{q2} \cdot CP_{t-1} + \beta_{q3} \cdot I_{t-1} + \beta_{q4} \cdot P_{t-1} + + \beta_{q5} \cdot SP_{t-1}$. If all the α_{pq}s are zero, the variable would be called weakly exogenous, meaning that this variable p does not respond to any long-run disequilibrium. Such a hypothesis is tested for each of the variables in the system, and the results are summarized in Table 3. Among the five variables, at a 5 percent significance level, weak exogeneity is rejected for corporate profits, the interest rate, and the S&P 500 index. However, weak exogeneity cannot be rejected for business failures and is rejected only marginally for the producer price index, implying exogeneity of these two variables, especially business failures.

Table 3. Weak exogeneity test on loading matrix α

	Null hypothesis	Chi-sq	p-value
F	$\alpha_{11} = \alpha_{12} = \alpha_{13} = 0$	5.01	0.17
CP	$\alpha_{21} = \alpha_{22} = \alpha_{23} = 0$	16.69	0.00
I	$\alpha_{31} = \alpha_{32} = \alpha_{33} = 0$	18.81	0.00
P	$\alpha_{41} = \alpha_{42} = \alpha_{43} = 0$	8.23	0.04
SP	$\alpha_{51} = \alpha_{52} = \alpha_{53} = 0$	9.81	0.02

Note: F stands for aggregate business bankruptcies, CP for corporate profits, I for the interest rate, P for the producer price index, and SP for the S&P 500 stock price index.

Based on the above short-run dynamics and weak exogeneity test results (also called short-run and long-run Granger causality, respectively), we can see that business failures do not appear to be an endogenous variable determined by the other four variables. Instead, business failures seem to be comparatively exogenous among the five. Nevertheless, the interrelationship discussed thus far does not go beyond Granger-type causality (the lead-lag relationship). We subsequently consider contemporaneous causality and the interactions among the variables in time profiles given by innovation accounting.

B. Contemporaneous causal flows for identification

From the estimated VECM, the innovation correlation matrix is also obtained, as shown in Table 4. In this matrix (only the lower triangle is shown), the correlations between F and I, CP and SP, and P and SP are among the strongest. The remaining correlations are much weaker. This correlation matrix is used as a starting point for uncovering possible contemporaneous causality, to be represented as a DAG pattern. The matrix is processed by TETRAD (Scheines et al. 1994) without a priori knowledge of causality among the five variables.

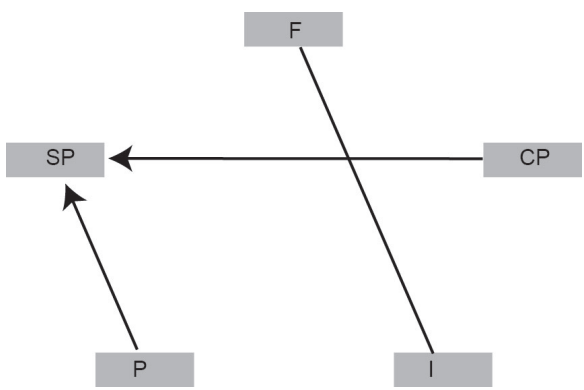
Table 4. Lower triangle of innovation correlation matrix

	F	CP	I	P	SP
F	1.000				
CP	0.028	1.000			
I	-0.264	-0.074	1.000		
P	-0.021	-0.063	0.089	1.000	
SP	-0.034	0.210	0.027	-0.234	1.000

Note: F stands for aggregate business bankruptcies, CP for corporate profits, I for the interest rate, P for the producer price index, and SP for the S&P 500 stock price index.

Using the PC algorithm, TETRAD proceeds with a complete set of undirected edges connecting each of the five variables to another. Edges are removed if a correlation or conditional correlation is not significantly different from zero for a given significance level. The remaining edges are directed by sepset conditions. The resulting directed graph, based on different levels of significance for the removal of edges, is given in Figure 2.

Figure 2. Directed graph pattern by PC algorithm



Note: Four significance levels (10, 20, 30, and 40 percent) are used and the results are the same across the four levels. F stands for aggregate business bankruptcies, CP for corporate profits, I for the interest rate, P for the producer price index, and SP for the S&P 500 stock price index.

Given the number of observations in this case, a significance level of 10 or 20 percent is appropriate (see the Monte Carlo results described in Spirtes, Glymour, and Scheines 2000). At either level, as shown in Figure 2, two directed edges are established. One directed edge shows a causal flow from CP to SP and the other is from P to SP. In addition, an edge exists between F and I, but it is not directed. For robustness, we go further to higher levels of 30 or even 40 percent (we understand that 30 percent is high by any hypothesis testing standards, yet it does allow us some idea of possible causal structures behind the data). Up to these levels, the DAG patterns are identical to those at the 10 and 20 percent levels.

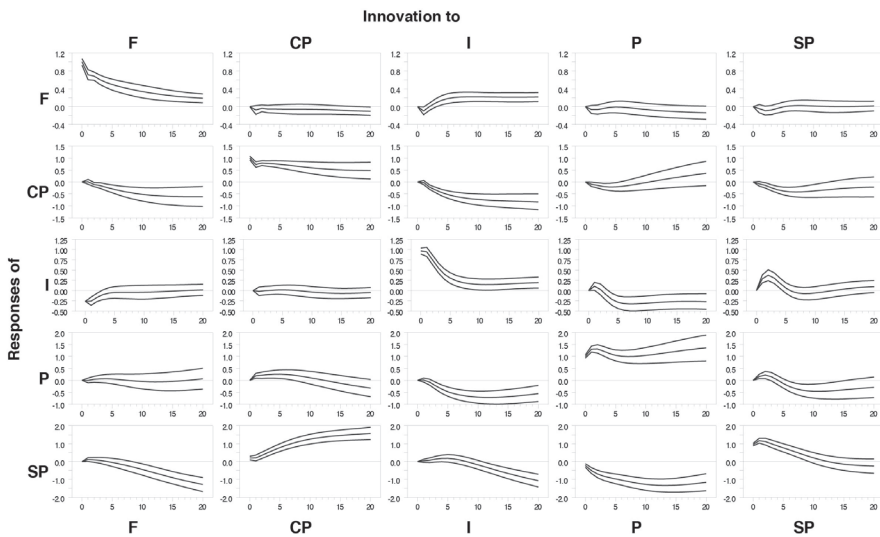
As for the undirected edge between F and I, insufficient information or a lack of true contemporaneous causality may be the reason for our inability to assign direction (this reason also explains the lack of direction between any two other variables). Given that we are unable to obtain a direction between F and I at usual significance levels, we test two alternative directions, namely, from F to I (directed by DAG at the 50 percent level) and from I to F. The following analysis results, impulse response function and forecast error variance decomposition, are shown to be almost identical between these two directions. The direction from F to I is chosen, given that it is the result supported by DAG, although at a higher significance level. This additionally directed edge and the two directed edges shown in Figure 2 define the contemporaneous causal structure to be used for VAR identification. For brevity, we may simply call this causal structure as the DAG-based causal structure in Figure 2 in the remainder of this paper.

C. Impulse response functions

The step from the DAG-based causal structure in Figure 2 to innovation accounting analysis follows the standard procedure in VAR. As in the case of Choleski and SVAR (Bernanke or Sims), the B_0 matrix (in Hamilton 1994, Chapter 11, notation) of contemporaneous relationship is first defined (restricted) based on the DAG contemporaneous causality and is used to estimate (identify) the underlying structural form of VAR model. With the structural model estimated (hence, the corresponding structural shocks), the innovation accounting analysis results are then computed.

Unlike the contemporaneous pattern revealed by the DAG, the impulse response functions presented in Figure 3 show the causal relationships over a horizon up to 20 quarters. The responses of all the five variables (normalized as each response is divided by the standard error of the corresponding innovation) to a one-time unit shock from itself or others, plus error bands, are shown in one of the 25 small graphs.[4] The variables undergoing shocks are listed on the top of the figure from column 1 to 5. The responses of the variables to each shock are shown in rows 1 to 5. We focus first on column 1 and row 1 to see how, in a qualitative sense, F influences other variables and how F is influenced by others.

Figure 3. Impulse response functions based on the causal structure in Figure 2



Note: F stands for aggregate business bankruptcies, CP for corporate profits, I for the interest rate, P for the producer price index, and SP for the S&P 500 stock price index. Each of the 25 small graphs in the figure represents the response of a variable to itself or another variable over a 20-quarter horizon. The responses of a variable to all variables (shown on the top of the figure) are shown in a single row from column 1 to 5. Alternatively, the responses of all the five variables to the same shock can be read in a single column from rows 1 to 5. For each response curve, the movement (response) of a variable has been normalized by dividing the response with the standard deviation of that variable.

[4] The error bands are likelihood-based bands as developed in Sims and Zha (1999) for overidentified SVAR. We use this method to provide a rough estimate for error bands in our structural VEC model.

In column 1, the response of CP to a shock in F is negative (a 2.7 percent drop)[5] and lasts over the 20-quarter horizon without dampening. SP responds negatively (with a 5 percent drop) to the shock in F, and the response becomes increasingly significant over time. Another variable affected by the F shock is I. I initially responds negatively (17 base points) to the F shock and is then back to normal roughly five quarters later. However, P basically does not respond to the F shock. While the effect from F to SP appears consistent with the firm-level failure phenomenon and is therefore easy to justify, the effects from F to CP and I appear more like a deviation from the group of studies started by Altman (1971, 1983). This deviation occurred because the effects of F on other variables are rarely addressed or simply assumed away from the beginning in the many studies since Altman (1971, 1983). Meanwhile, the effects found in this study are more in line with Liu (2009). Based on the flexible VAR framework that allows for mutual causality, Liu (2009) found that business failure rate exerts influence on all other five variables, namely, interest rate, credit, corporate profits, inflation, and business births. However, compared with Liu (2009), our result shows that the mutual influences between business failures and inflation are weak and so is the influence from business failures to interest rate.

The responses of F to the shocks from the other four variables are shown in row 1. A positive CP shock has a negative impact on F, but it is almost negligible in magnitude and does not appear to be statistically significant. The P and SP shocks have similarly negligible effects on F. However, F shows a positive response (a 1.5 percent increase) to I, and this response lasts into a long horizon. For this section of results, given that most previous studies focused on the effects of macro variables on business failures, a comparison of our results to theirs is easier to make. Among others, Altman (1983) found that reduced economic growth, negative stock market performance, and slower money supply all contribute to higher business failure propensity. In addition, Liu (2004, 2009) found that higher price level leads to a higher business failure rate via the channel of higher input cost and nominal interest rate. Compared with these studies, our results do not confirm any significant effect from CP, P, and SP. However, our result does show that a

[5] Other than the responses in terms of standard deviation shown in Figure 3, the numbers (in percentage or base point) in this bracket and in three other brackets are the translated values based on the estimated standard deviation and calculated sample averages for particular variables. For example, a 2.7 percent drop in CP is translated from a 0.6 standard deviation drop, given that one standard deviation in CP corresponds to 25.9 billion dollars, and the average CP over the sample period is 571 billion. These numbers are given particularly for the effects of F on CP, SP, and I and for the effect of I on F (covered in the immediately following paragraph) to offer a rough yet probably more realistic assessment.

higher interest rate results in more business failures. This finding lends support to some previous studies (Melicher and Hearth 1988; Liu 2004, 2009), indicating the importance of credit availability and cost to the survival of marginal firms, and further, the role of interest rate as a potential instrument when the control of bankruptcy risk is the policy target.

Although not the focus of this paper, the interactions among the other four variables can also be observed when we go through shock-delivering columns 2 to 5 and see their effects on rows 2 to 5. First, a shock to CP has limited effect on I, whereas this shock leads to a significant increase in SP, and a short-term increase in P followed by a decrease over time. Compared with CP, SP appears to be somewhat more influential. A shock to SP induces a negative response from CP to a certain degree, and positive responses from I and P in a short horizon that are followed by decreases over a longer horizon. Finally, a positive shock to I and P seems to have overall negative effects on all other variables, except that in response to a P shock, I first increases in a very short run (roughly two or three quarters) and then decreases afterwards.

D. Forecast error variance decomposition

Table 5 presents the forecast error variance decomposition results. Listed in the table for each variable (in one section) are six steps at 0 (contemporaneous time), 1, 2, 5, 10, and 20 quarters ahead. For each step, the entries show the percentage of variation in a variable that is due to innovations by itself and the other four variables. In addition to impulse response functions, forecast error variance decomposition offers an alternative way to look at the relative exogeneity (or endogeneity) of the variables more precisely.

Much like what we did with impulse response function results in the preceding subsection, we first examine the effects of the F shock on all variables by looking at column 1 (corresponding to F) across all five sections. First, a shock to F consistently explains significant proportions of its own variance across different horizons, as high as 81 percent even by the end of the 20-quarter horizon. Further, as to the effects on the other four variables, the F shock explains increasing proportions of CP variance (up to 19 percent) and SP variance (up to 12 percent) over the 20-quarter horizon. On the contrary, the effects of the F shock on I and P are limited. In the very short term (up to two quarters), 6 percent of I variance is attributed to F, and this drops roughly 4 percent in a longer horizon. The portion of P variance attributed to the F shock is even smaller and can be neglected.

Table 5. Forecast error variance decomposition based on the causal structure in Figure 2

Step	F	CP	I	P	SP
F					
0	100.0	0.0	0.0	0.0	0.0
1	98.7	0.3	0.6	0.3	0.1
2	98.4	0.3	0.4	0.4	0.5
5	96.3	0.5	2.3	0.3	0.6
10	90.8	0.8	7.5	0.5	0.5
20	80.7	1.8	14.3	2.7	0.4
CP					
0	0.0	100.0	0.0	0.0	0.0
1	0.0	99.0	0.0	0.6	0.4
2	0.5	94.9	2.1	1.3	1.2
5	3.2	75.1	12.3	3.0	6.4
10	10.1	52.6	25.3	2.0	10.0
20	18.6	34.2	36.7	3.0	7.5
I					
0	7.0	0.0	93.0	0.0	0.0
1	6.7	0.0	88.9	0.5	3.9
2	5.9	0.0	85.7	0.4	8.0
5	5.0	0.0	81.1	4.2	9.7
10	4.4	0.1	71.7	15.3	8.5
20	3.6	0.8	62.2	26.0	7.4
P					
0	0.0	0.0	0.0	100.0	0.0
1	0.0	1.3	0.0	97.7	1.0
2	0.0	1.8	0.1	96.4	1.6
5	0.1	3.0	4.6	91.0	1.3
10	0.1	2.6	14.5	77.7	5.1
20	0.1	2.1	17.9	73.8	6.2
SP					
0	0.0	3.9	0.0	4.9	91.2
1	0.5	3.0	0.1	11.3	85.2
2	0.5	4.5	0.2	17.1	77.7
5	0.3	14.0	0.9	29.7	55.2
10	1.9	30.1	0.6	39.8	27.6
20	12.3	37.3	7.2	33.9	9.3

Note: F stands for aggregate business bankruptcies, CP for corporate profits, I for the interest rate, P for the producer price index, and SP for the S&P 500 stock price index. Steps are in quarters. In each of the five sections, the decomposition results for each variable are shown at six selected steps from 0 (contemporaneous) to 20. For each step (in a row), the decompositions sum up to 100. Each component of the decompositions means the percentage of variance that is due to a variable itself or the other variables (shown in columns 1 to 5).

Next, we examine how F responds to shocks from itself and the other four variables by looking at columns 1 to 5 of the first section in Table 5. As before, each entry represents the variance decomposition at a particular moment, and the numbers across columns sum up to 100. Contemporaneously, 100 percent of F variance is attributed to itself. This is the case because F has been identified as a cause in contemporaneous time as established earlier by DAG. Over time, the effects of the other four variables kick in, and they explain varying yet largely growing percentages of the F variance. Particularly, the I shock is the most influential. By the 10th quarter, 8 percent of the F variance is attributed to the I shock, and the percentage rises to 14 by the 20th quarter. The effect of P is far more modest, followed by the negligible effects of CP and SP.

Overall, we can see that the patterns are consistent with what is shown by impulse response functions, that is, F can exert some influence on three other variables, CP, I, and SP, but it is not significantly influenced by the other variables, except I. Between F and I, the I shock is the primary reason for the F variance, other than its own shock. On the contrary, for I variance, the primary reason is the P shock, followed by SP, and then F. In other words, interest rate responds to a relatively wide set of factors, including inflation, stock market performance, and business failures, whereas business failures respond primarily to interest rate only, suggesting the relatively greater role of interest rate when compared with business failures.

V. Conclusion

Previous studies typically sought to determine the effect of macroeconomic conditions on aggregate business failures based on firm-level phenomena, implying an incomplete one-way causality. Arguing that business failures at the aggregate level should be modeled beyond our thinking about firm-level failure, i.e., the possible causality from business failures to macro conditions should be allowed, we have instead studied this issue in a cointegrated VAR built on DAG, a tool for data-driven causality identification. Based on such a data-driven framework, the interrelationship among aggregate business failures, aggregate corporate profits, interest rate, inflation, and stock market performance are examined for the case of the U.S. using quarterly data between 1980 and 2004, a period covered by the Bankruptcy Reform Act of 1978.

A central finding of our analysis is the exogeneity of aggregate business failures, i.e., aggregate business failures are not influenced much by other variables,

except that a positive shock to interest rate causes a lasting rise in business failures. Furthermore, a rise in business failures causes significant drops in corporate profits, stock market performance, and to a lesser degree, interest rate. This finding, especially the causal flows from business failures to macro variables, lends support to the mechanism proposed by Bernanke (1981), who showed that business failure risk can play a structural role in economic fluctuations. Based on that mechanism, rising bankruptcy risk makes all agents in the economy cautious. As a result, consumers and firms cut or defer their purchasing, whereas lenders become more selective and limit the size of their loans, which, in turn, deepens a recession.

In a broader view, the results in this study relate to the wider scope of literature regarding the effect of corporate financial conditions on macroeconomic conditions (e.g., Fazzari, Hubbard, and Petersen 1988, Carpenter, Fazzari, and Petersen 1994, Gilchrist and Himmelberg 1995, among others). Particularly, as summarized in Bernanke, Gertler, and Gilchrist (1998), from a perspective that gives a central role to credit market conditions in economic fluctuations, "deteriorating credit-market conditions – sharp increases in insolvencies and bankruptcies, rising real debt burdens, collapsing asset prices, and bank failures – are not simply passive reflections of a declining real economy, but are in themselves a major factor depressing economic activity." To our knowledge, few previous studies contain direct evidence for the causal effect from business failures to economic fluctuations. The result documented in this work, along with that in Liu (2009), may be viewed as supplying such evidence confirming the proactive role of bankruptcies. In this perspective, the policy implication of our findings goes beyond business failures. It actually takes us back to the general story regarding the role of monetary policy as a credit policy in stabilizing the economy. Such a general context should be the policy background against which policy makers think about the best responses to business failure risk in the use of monetary instruments.

References

Altman, Edward I. (1971), *Corporate bankruptcy in America*, Lexington, MA, Heath Lexington Books.

Altman, Edward I. (1983), Why businesses fail, *Journal of Business Strategy* **3**: 15-21.

Awokuse, Titus O., and David A. Bessler (2003), Vector autoregressions, policy analysis, and directed acyclic graphs: An application to the U.S. economy, *Journal of Applied Economics* **6**:1-24.

Bernanke, Ben S. (1981), Bankruptcy, liquidity, and recession, *American Economic Review* **71**: 155-9.

Bernanke, Ben S. (1986), Alternative explanations of the money-income correlation, *Carnegie-Rochester Conference Series on Public Policy* **25**: 49-100.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist (1998), The financial accelerator in a quantitative business cycle framework, Working Paper 6455, NBER.

Bessler, David A., and Jian Yang (2003), The structure of interdependence in international stock markets, *Journal of International Money and Finance* **22**: 261-87.

Carpenter, Robert E., Steven M. Fazzari, and Bruce C. Petersen (1994), Inventory investment, internal finance fluctuations, and the business cycle, *Brookings Papers on Economic Activity* **2**: 75-122.

Chava, Sudheer, and Robert A. Jarrow (2004), Bankruptcy prediction with industry effects, *Review of Finance* **8:** 537-69.

Demiralp, Selva, and Kevin D. Hoover (2003), Searching for the causal structure of a vector autoregression, *Oxford Bulletin of Economics and Statistics* **65**: 745-67.

Fazzari, Steven M., R. Glenn Hubbard, and Bruce C. Petersen (1988), Financing constraints and corporate investment, *Brookings Papers on Economic Activity* **1**: 141-95.

Gilchrist, Simon, and Charles P. Himmelberg (1995), Evidence on the role of cash flow for investment, *Journal of Monetary Economics* **36**: 541-72.

Hamilton, James D. (1994), *Time series analysis*, Princeton, NJ, Princeton University Press.

Hansen, Henrik, and Katarina Juselius (1995), CATS in RATS: Cointegration analysis of time series, Evanston, IL, Estima.

Hudson, John (1986), An analysis of company liquidations, *Applied Economics* **18**: 219-35.

Johansen, Soren (1991), Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models, *Econometrica* **59**: 1551- 80.

Liu, Jia (2004), Macroeconomic determinants of corporate failures: evidence from the UK, *Applied Economics* **36**: 939- 45.

Liu, Jia (2009), Business failures and macroeconomic factors in the UK, *Bulletin of Economic Research* **61**: 47-72.

Melicher Ronald W., and Douglas Hearth (1988), A time series analysis of aggregate business failure activity and credit conditions, *Journal of Economics and Business* **40:** 319- 33.

Pearl, Judea (1986), Fusion, propagation, and structuring in belief networks, *Artificial Intelligence* **29**: 241- 88

Platt, Harlan D., and Marjorie B. Platt (1994), Business cycle effects on state corporate failure rates, *Journal of Economics and Business* **46**: 113- 27.

Rose, Peter S., Wesley T. Andrews, and Gary A. Giroux (1982), Predicting business failure: a macroeconomic perspective, *Journal of Accounting, Auditing, & Finance* **6**: 20-31.

Scheines, Richard, Peter Spirtes, Clark Glymour, and Christopher Meek (1994), *TETRAD II: user's manual and softwar*e, New Jersey, NJ, Lawrence Erlbaum Associates, Inc.

Sims, Christopher A. (1980), Macroeconomics and reality, *Econometrica* **48**: 1-48.

Sims, Christopher A. (1986), Are forecasting models usable for policy analysis?, *Federal Reserve Bank of Minneapolis Quarterly Review* **10**: 2-16.

Sims, Christopher A. and Tao Zha (1999), Error bands for impulse responses, *Econometrica* **67**: 1113-55.

Spirtes, Peter, Clark Glymour, and Richard Scheines (2000), *Causation, prediction, and search*, Cambridge, MA, MIT Press.

Swanson, Norman R., and Clive W.J. Granger (1997), Impulse response functions based on a causal approach to residual orthogonalization in Vector Autoregression, *Journal of the American Statistical Association* **92**: 357-67.

Wadhwani, Sushil B. (1986), Inflation, bankruptcy, default premia and the stock market, *Economic Journal* **96**: 120-38.

Journal of Applied Economics. Vol XVI, No. 1 (May 2013), 179-202

AGGREGATE BUSINESS FAILURES AND MACROECONOMIC CONDITIONS: A VAR LOOK AT THE U.S. BETWEEN 1980 AND 2004

Jin Zhang*
Southwestern University of Finance and Economics

David A. Bessler and David J. Leatham
Texas A&M University

Submitted April 2010; accepted May 2012

In this paper, we study the U.S. aggregate business failures during 1980- 2004 in relation to four macroeconomic variables: aggregate corporate profits, the producer price index, the interest rate, and stock market performance. We argue that aggregate business failures should not be treated as a passive variable, as usually done in previous studies, and we allow its possible causal effect on other macroeconomic variables through a Structural Vector Autoregression model that builds on Directed Acyclic Graphs. Granger type causality and innovation accounting results both show that while subject to the influence of interest rates, aggregate business failures are quite exogenous in comparison to the other three variables. The implications of these findings are discussed as well.

JEL classification codes: C32, E51, G33
Key words: business failures, macroeconomic conditions, directed acyclic graphs, vector autoregression

---

* Jin Zhang (corresponding author): Research Institute of Economics and Management, Southwestern University of Finance and Economics, Chengdu, Sichuan 610074, China; e-mail: jin.zhang@swufe.edu.cn. David A. Bessler: Department of Agricultural Economics, Texas A&M University, Colleges Station, TX 77843; e-mail: d-bessler@tamu.edu. David J. Leatham: Department of Agricultural Economics, Texas A&M University, College Station, TX 77843; e-mail: d-leatham@tamu.edu. We would like to thank one co-editor and two anonymous referees for the many helpful comments and suggestions. All errors are ours.

I. Introduction

The issue of business failures (or bankruptcies, interchangeably) has drawn extensive attention over the past half century, which is not surprising given the huge costs usually associated with business failures. The vast majority of the literature on this issue deal with business failures at the micro level, especially the prediction of individual business failures based on firm-specific information. At the macro level, there is a line of research that addresses the overall business failures in an economy and its relationship with other macroeconomic conditions, but it is far less extensive than those at the micro level, both theoretically and empirically.

The macro line of research on business failures was started by Altman (1971, 1983). In his studies, Altman first identified a set of macro variables that are likely to cause the failure of individual firms, including economic growth, credit or money market conditions, stock market activity, and business population characteristics. He then tested the possible causal effects on aggregate business failures in a distributed-lag regression model based on U.S. data. Since then, others have updated the research along this line, including Rose, Andrews, and Giroux (1982), Hudson (1986), Wadhwani (1986), Melicher and Hearth (1988), Platt and Platt (1994), and more recently, Liu (2004, 2009). Roughly speaking, these empirical studies have reached a consensus on the effects of certain variables on business failures, notably, corporate profits and interest rates. However, they have conflicting opinions on other variables, especially the price level and stock market performance. The potential reasons for differing results range from different samples (different periods in different countries, hence potentially different economic structures and institutional backgrounds) to the conceptual frameworks, and methodology adopted.

In this study, we re-examine the relationship between business failures and macroeconomic conditions for the case of the United States. As a first motivation of this study, we examine the post-1980 period to provide a more recent and relevant coverage. Unlike other economic events or variables, bankruptcy, either personal or business, is also a legal phenomenon, governed directly by corresponding legal procedures. Aggregate business failures are inevitably subject to the influence of changes in legal systems (see Liu 2004 for the empirical evidence in the case of the U.K.). Since the early 20th century, the U.S. bankruptcy legal system was defined first by the Bankruptcy Act of 1938. Then the Bankruptcy Reform Act of 1978 came into effect and changed the legal environment of bankruptcy

substantially. Among the limited studies on the U.S. case, however, no paper has effectively covered the issue for the period since 1980. To reflect a more relevant reality, we choose to study the relationship between business failures and macro conditions for the period from 1980 to 2004. On one end, we choose 1980 as the beginning because it is the first year following the passage of the Bankruptcy reform Act of 1978 on October 1, 1979. On the other end, we choose not to extend the coverage beyond 2004, to avoid the complication (structural change) that may be caused by the more restrictive bankruptcy code (the Bankruptcy Abuse Prevention and Consumer Protection Act of 2005) and the turbulent financial crisis that immediately followed.

Second, as a further motivation, we feel that the approach usually followed in the existing literature emphasizes the one-way causality from other variables to aggregate business failures, but the reverse causality from aggregate business failures is largely ignored, which leaves the whole picture incomplete. Since Altman (1971), studies in this context usually begin with an intention to find what determines business failures, and macro variables are identified as potential determinants if they are believed to influence the failure of individual firms. The issue is, even if the causality from macro variables to individual business failures is true, it is questionable whether we can apply this relationship to the macro level, i.e., to aggregate business failures. By using the macro conditions thus identified as the right-hand-side variables and estimating their effects on aggregate business failures with the usual regression methods, the potential exogeneity of aggregate business failures or its causal flows to other variables is a priori ruled out. Conceptually, aggregate business failure may not be such a passive variable; instead, it may play a proactive role in the overall economy (Bernanke 1981). Therefore, a more flexible framework should be employed to allow for this possibility.

The more flexible framework we employ in this study is Vector Autoregression (VAR) that builds on a data-determined identification from Directed Acyclic Graphs (DAG). VAR (Sims 1980) is an econometric framework flexible enough in the sense that all variables considered are treated as potentially endogenous. Only minimal assumption on structure is needed, which makes VAR a good candidate for the issue at hand, given that the causal structures among variables are unclear. To date, VAR has not been used to study this issue, except in Liu (2009) wherein the case of the U.K. was studied in the setting of Vector Error Correction (VEC). For VAR to be useful for policy analysis, the underlying structure has to be identified, and the identification methods of Choleski and Structural VAR (SVAR;

Sims 1986; Bernanke 1986) have been widely used. Rather than following these two approaches, we rely on DAG and the inductive causality algorithms to provide a "data-driven" causal structure for identification. With an origin in artificial intelligence and computer science, this "data-driven" approach does not make a prior assumption on causal structure, but instead produces the structure from data. Therefore, this approach may produce a more objective analysis than those based on Choleski decomposition or a structural model based on subjective grounds (Swanson and Granger 1997). In the remainder of this paper, Section II introduces the conceptual framework and data. A description of econometric methods follows in Section III. Section IV presents the empirical implementation, as well as the results and discussions. Section V concludes.

II. Conceptual framework and data

We first identify a variable to represent the business failure activity at the macro level. Primarily two measures have been used in the literature to describe aggregate business failures, i.e., the business failure rate in percentage (e.g., Altman 1983), and the business failures in numbers (e.g., Melicher and Hearth 1988). Compared with the latter, the business failure rate gives clearly an unconditional probability of failures for firms in the economy; however, for the U.S., the influential Dun & Bradstreet business failure rate used in previous studies was discontinued after 1997. Yet, at the same time, as business failures (and births, too) account for a very small portion of total active firms (no more than 2 percent per annum, even in the worst years), the business failures in numbers mimics closely the time series pattern of the business failures in percentage (Chava and Jarrow 2004). Given the purposes of this study, where our interest is essentially focused on the dynamic pattern of business failure activity and its relationship with other variables, we choose the business failures in numbers to enable coverage up to 2004.

We then identify relevant macroeconomic variables by examining the effects of a list of macro variables on a firm's propensity to fail. Such an examination suggests that particular macroeconomic variables potentially influence business failures, including economic growth, monetary conditions, inflation, and stock market performance. This approach, which identifies related macro variables, is essentially the same as that used in Altman (1983), Liu (2004, 2009), and Platt

and Platt (1994), among others.[1] Before we deviate from existing studies in the following econometric analysis, the content of such an examination for macro variable identification is laid out in the following four paragraphs.

First, economic growth is considered important because it may have a direct influence on a firm's sales and earnings. Sales and earnings are two direct and important measures of a firm's current performance and provide the cash flow critical to the firm's continued survival. An overall economic index, such as gross national product or aggregate corporate profits, may be used for this condition (Altman 1983). We choose aggregate corporate profits because they measure the business health of firms directly. This variable is used extensively in the literature and has usually been found significant and negatively associated with business failures.

Money, or credit availability and its cost, is another factor believed to have a direct impact on the survival of a marginal firm. "Regardless of how poorly a firm is performing, it seldom is motivated to declare bankruptcy as long as liquidity is sufficient or credit is available" (Altman 1983). It is then reasonable to expect that the aggregate business failures will increase as credit conditions become tighter. Following the literature, we choose interest rates to capture monetary conditions.

The effect of inflation on aggregate business failures is less clear. Inflation is generally an important indicator of the overall economy, and its effect on business failures may be twofold. On one hand, as Altman (1983) postulated, inflation, especially unanticipated price increases, "tend to be inversely correlated with failure rates," because leveraged firms can repay their debts with "cheaper" money, and also because inflation may cause reduced competitiveness. On the other hand, inflation may result in more failures as it makes the earnings of a firm more volatile and harms its capability to repay its debt (Wadhwani 1986). Some evidence (Wadhwani 1986; Liu 2004, 2009) suggests that inflation leads to more business bankruptcies. Thus, inflation is included as a third variable that may affect aggregate business failures.

Stock market performance is the fourth factor that we consider. The stock price of a firm is usually believed to reflect the firm's economic value, whereas

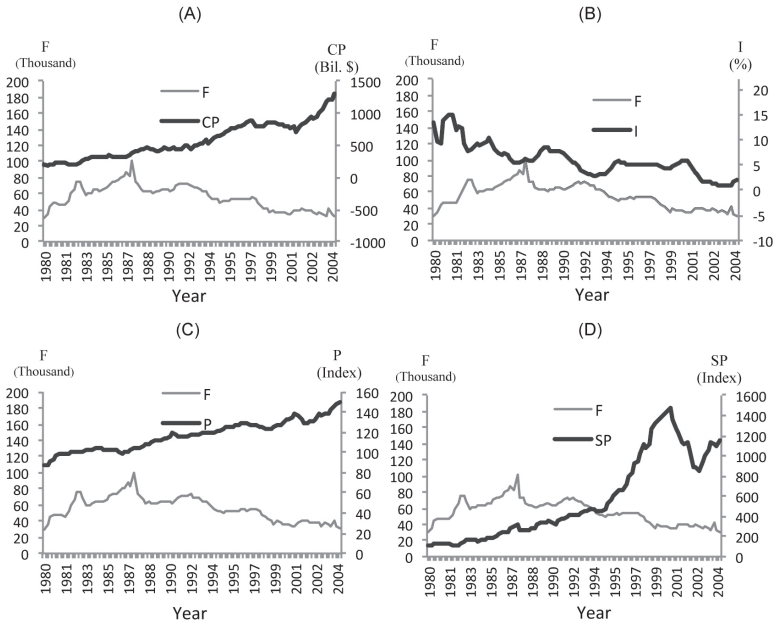
[1] Although these studies all identify macro variables by starting with an examination of individual firm failure, the macroeconomic variables selected in each study vary. The variables chosen in our study are closer to those in Altman (1983) and Liu (2004, 2009). Compared with these two studies, we place less emphasis on the composition of business failures and do not include new firm formation variables. In the meantime, we include inflation (compared with Altman 1983) and stock market performance (compared with Liu 2004, 2009).

stock price indices, such as the S&P 500 stock price index, indicate the overall expectation about the future of the whole economy. Altman (1983) argued that stock market performance affects firm failures because a potential failing firm will not go bankrupt "if the future appears hopeful," as indicated by investor expectations or stock market performance. For the same reason, a falling stock price, indicative of a firm's falling economic values, may also increase a firm's propensity to fail. At the aggregate level, both stock market performance and aggregate business failures are labeled as leading indicators, but which of the two causes the other is another issue. Among existing studies (Rose, Andrews, and Giroux 1981; Altman 1983; Melicher and Hearth 1988), the effect of stock market performance, as represented by the S&P 500 stock price index, on business failures has been found significant, with inconsistency regarding the sign. The possible causality in the reverse direction, i.e., the effect of business failures on stock market performance, should also be allowed, and we let data tell us if this possible effect is true.

Five U.S. quarterly data series, measured over 1980 to 2004 with a total of 100 observations, are used to represent the five variables discussed above.[2] The number of total business bankruptcies (F) is used to measure the aggregate business failures in the U.S. The other four variables, i.e., corporate profits (CP), the 3-month T-Bill yield (I), the producer price index of all commodities (P), and the S&P500 stock price index (SP), are used to reflect economic growth, money supply and credit conditions, the price level, and investor expectations, respectively. The five data series have been obtained from the following sources: the number of total business bankruptcies from the Office of U.S. District Courts, corporate profits from the Bureau of Economic Analysis, the 3-month T-bill yield from the Federal Reserve Bank, the producer price index of all commodities from the Bureau of Labor Statistics, and the S&P 500 stock price index from Standard & Poor's. A graphical presentation of all five variables is given in Figure 1, with business failures presented against each of the other four macroeconomic variables. The ordinary correlations between aggregate business failures and corporate profits, the T-Bill yield, the producer price index, and the S&P 500 stock price index are -0.697, 0.269, -0.637, and -0.736, respectively, which are all significant at the 1 percent level. These correlations are largely consistent with the relationships hypothesized above. However, we are unable to say much about the causality among the five variables without further analysis.

[2] The three-month T-Bill yield and producer price index of all commodities were originally monthly data and were transformed into quarterly data by taking the average of the monthly figures.

Figure 1. Movements of aggregate business failures against four macro variables



Note: In the four small graphs, the vertical axis on the left hand side corresponds to aggregate business bankruptcies (F), while the vertical axis on the right hand side is used for corporate profits (CP), the interest rate (I), the producer price index (P), and the S&P 500 stock price index (SP), respectively. In terms of units, F is in number of thousands, CP in billions of dollars, I in percent, P and SP in index as usually defined. To distinguish the line for F from those for other four variables, the lines for the other four variables are shown in bold.

As a preliminary analysis, the five data series are each tested for stationarity using augmented Dickey–Fuller (ADF) and Phillips–Perron (PP) tests. The null hypothesis of both tests is that the series tested is nonstationary. As reported in Table 1, by the ADF test, nonstationarity cannot be rejected at the 5 percent level for both the case of trend and the case of no trend for all five series. The PP test also finds the data series to be nonstationary. Further tests on the first differences of these data suggest them to be stationary. Therefore, all five series are treated as I(1) in the following analysis.

Table 1. ADF and PP tests for nonstationarity

Series	ADF		PP	
	Without trend	With trend	Without trend	With trend
Variables in level				
F	-0.98	-3.46	-1.51	-3.44
CP	1.36	-1.37	1.39	-1.61
I	-1.48	-2.97	-2.15	-3.05
P	-0.10	-2.93	-0.32	-2.76
SP	-0.47	-2.01	-0.54	-2.03
Variables in first difference				
F	-11.31	-11.53	-11.22	-11.43
CP	-10.26	-10.48	-10.35	-10.52
I	-8.73	-8.67	-8.76	-8.70
P	-6.15	-6.14	-6.16	-6.13
SP	-6.07	-6.05	-6.17	-6.15

Note: F stands for aggregate business bankruptcies, CP for corporate profits, I for the interest rate, P for the producer price index, and SP for the S&P 500 stock price index. ADF is a unit root test developed by Dickey and Fuller. PP is a unit root test developed by Phillips and Perron. Critical values for the ADF test at 5 percent level with constant only and with constant and trend are -2.89 and -3.46, respectively. Critical values for the PP test at 5 percent level with constant only and with constant and trend are -2.891 and – 3.456, respectively. For both tests, nonstationarity is rejected when calculated values are less than critical values.

III. Methodology

Given the data being I(1), we consider a cointegrated VAR that allows for possible cointegration among the five variables. Let Y_t denote the vector that contains the five studied variables. Assuming for now the existence of cointegration, the system of five variables can then be described below by a VEC Model (VECM), as developed by Johansen (1991):

$$\Delta Y_t = \Pi Y_{t-1} + \sum_{i=1}^{k-1} \Gamma_i \Delta Y_{t-i} + \mu + \Psi Z_t + e_t \quad , \tag{1}$$

where $t = 1,...,T$, Δ is the difference operator ($\Delta Y_t = Y_t - Y_{t-1}$), Π is a $N \times N$ matrix ($N = 5$ in this case) of coefficients for long run relationship, k is the lag length for the VAR of undifferenced variables, Γ_i is a $N \times N$ matrix of coefficients for the i_{th} lagged period, μ is a $N \times 1$ vector of constant, Ψ is the coefficient matrix associated with exogenous variables Z_t , and e_t is a $N \times 1$ vector of residuals.

From the above data generation process, we can obtain the interrelationship between variables from different perspectives. First, based directly on the estimated VECM in equation (1), the short-run Granger dynamics can be read from Γ_i; also available from equation (1) is the long-run relationship among the possible cointegrated variables from Π. Further, from e_t or its covariance matrix, the contemporaneous causal structure can be derived via DAG. Finally, based on contemporaneous causality as the identification condition for SVARs, the short-run relationship can be summarized through the innovation accounting techniques, i.e., impulse response function (IRF) and forecast error variance decomposition (FEVD). Although VECM models the variables in their first differences, after transformation, the relationship given by innovation accounting is actually in terms of the original level variables, as shown below:

$$Y_t = (I + \Pi + \Gamma_1)Y_{t-1} - \sum_{i=1}^{k-2}(\Gamma_i - \Gamma_{i+1})Y_{t-i-1} - \Gamma_{k-1}Y_{t-k} + \mu + \Psi Z_t + e_t \quad , \tag{2}$$

where I is an identity matrix of $N \times N$ ($N = 5$ in this case). In the remainder of this section, we explain particularly the DAG-based contemporaneous causal structure for VAR identification.

A. VAR identification based on contemporaneous causal structure

For innovation accounting analysis to reveal the causal relationships among the variables in the VAR system, identifying structural shocks from observed residuals is important. The identification approach suggested by Sims (1980) relies on the Choleski decomposition of contemporaneous correlation (covariance matrix) of residuals. However, the recursive contemporaneous causal ordering implied in Choleski decomposition is simply too restrictive, oftentimes not true, and thus misleading. Therefore, SVAR has been suggested as a decomposition that can incorporate a more flexible prior causal structure (Sims 1986, Bernanke 1986). Early proponents of the SVAR used a prior theory to suggest a structural decomposition. Nevertheless, the problem is not solved if a causal structure is not available from theory, or even if we have one but it is not objective (Swanson and Granger 1997).

More recently, a data-determined SVAR framework has been advocated by Swanson and Granger (1997) and Demiralp and Hoover (2003), and applied by Awokuse and Bessler (2003), and Bessler and Yang (2003), among others. In this framework, DAG, a method of causal inference, is used to provide the contemporaneous causal order required in a SVAR. The issue we study in this

paper represents exactly a situation where no predetermined (theoretical) contemporaneous causal structure can be used. A data-driven approach that does not assume a priori knowledge of causality is justified. We discuss such a data-driven DAG method below.

B. Directed acyclic graphs

Directed graph, developed in computer science, represents a graphical way to describe the causal flows among a set of variables. A directed graph can formally be described as a triple (V, M, E), where V is a non-empty set of vertices standing for variables studied, e.g., a set of five vertices for the five variables in this study; M is a non-empty set of symbols (usually arrowhead or empty) attached to the ends of undirected edges; and E is a set of ordered pairs defining the combination of vertex and symbol for the ends of undirected edges (Spirtes, Glymour, and Scheines 2000). Consider two variables A and B among a set of variables V. Probably the most interesting information out of a directed graph is a directed edge, such as $A \rightarrow B$, indicating that variable A causes variable B. However, a directed edge is not the only possibility. Other types of edges, bi-directed ($A \leftrightarrow B$) and undirected ($A - B$), may also appear in a directed graph, suggesting mutual causality or lack of information to direct causality. Among directed graphs, DAG, a graph type that contains no cyclic paths of causal flows, is the type suitable for this study.

In a statistical sense, DAGs are designs to express conditional independence. As a graphical way to characterize conditional independence, the notion of D-separation (dependence separation) was proposed by Pearl (1986), and it has been incorporated into the algorithms for building directed graphs, especially the PC algorithm. Details on this basic PC algorithm and its derivatives can be found in Spirtes, Glymour, and Scheines (2000). Very briefly, from an operational perspective, to produce a DAG, the algorithm begins with a complete undirected graph, wherein an undirected edge exists between every two variables (contained in V). Then, the undirected edges between variables are removed sequentially in case of zero correlation or partial correlation (conditional correlation), as tested using Fisher's z. Finally, the remaining undirected edges are assigned a direction (directed) using the concept of sepset.[3]

[3] Consider for concreteness a set of three variables connected as $X - Y - Z$, wherein the edge between X and Z has already been removed. The sepset means the conditioning variable(s) for the removed edge between X and Z. To use sepset, if Y is not one of the variables in X and Z's sepset, then the direction can be assigned as $X \rightarrow Y \leftarrow Z$.

Based on the Monte Carlo simulations of the PC algorithm (Spirtes, Glymour, and Scheines 2000; Demiralp and Hoover 2003), for sample sizes of 100, the PC algorithm may exclude (or include) edges incorrectly and/or probably more likely assign the directions of edges incorrectly. Spirtes, Glymour, and Scheines (2000, p. 116) pointed out, "In order for the methods to converge to correct decisions with probability 1, the significance level used in making decisions should decrease as the sample size increases and the use of higher significance levels (e.g., 0.2 at sample size less than 100, and 0.1 at sample size between 100 and 300) may improve performance at small sample sizes." Based on their suggestions, the DAG results at various significance levels, from 0.1 to higher, are explored in the present study.

IV. Results and discussions

Having previously established in Section II that the five variables used in this study are I(1), we model them in VECM and interpret the estimated model in terms of short-run and long-run (Granger type) causality. DAG will then be applied to use the VECM residual information to obtain the contemporaneous causal structure. After obtaining this causal structure, the structural VECM underlying the reduced VECM is estimated or identified, and further, transformed into the usual VAR model in level variables. Finally, the IRF and FEVD analyses are carried out to reveal the interactions among the original level variables instead of their first differences.

To build this VECM, the optimal lag length for a VAR of the five variables in their first differences is obtained by minimizing Schwarz and Akaike loss criteria. Specifically, the Schwarz and Akaike loss criteria give the optimal lag of 1 and 3, respectively. A lag of 1 would be preferable based on the parsimony principle. In addition, subsequent LM tests of the VECM model based on the lag of 1 suggests no presence of autocorrelation in the residuals. Thus, the lag of 1 is chosen. We then verify the existence of cointegration in the variables using the trace test of Johansen. As shown by the results reported in Table 2, three cointegration vectors with a linear trend exist among the five variables.

Table 2. Trace test statistics for the studied variables

r	Without linear trend			With linear trend		
	T	C(5%)	C(10%)	T	C(5%)	C(10%)
=0	124.21	75.74	71.66	100.68	68.68	64.74
<=1	73.47	53.42	49.92	53.64	47.21	43.84
<=2	40.51	34.80	31.88	32.25	29.38	26.70
<=3	21.03	19.99	17.79	13.63	15.34	13.31
<=4	5.90	9.13	7.50	1.21	3.84	2.71

Note: The trace test indicates the number of cointegration vectors (r) for cases with and without constant. The critical values (C) at the 5 and 10 percent levels are as given in Hansen and Juselius (1995). To determine the number of cointegration vectors, we start with the top row and move from the left column of "with constant" to the right column of "without constant." This process continues to the next row until we meet the first "fail to reject" case, i.e., when the trace test statistic (T) is less than the critical value (C).

The VECM model with three cointegration vectors and trend in the series are estimated (with t-statistic in parenthesis), as shown in the equation:

$$\begin{bmatrix} \Delta F_t \\ \Delta CP_t \\ \Delta I_t \\ \Delta P_t \\ \Delta SP_t \end{bmatrix} = \begin{bmatrix} 6885.59 \\ (0.66) \\ 293.13 \\ (4.46) \\ 7.59 \\ (4.52) \\ 9.51 \\ (3.27) \\ 125.16 \\ (1.50) \end{bmatrix} + \begin{bmatrix} -0.22 & -11.76 & -1033.48 & -227.44 & -4.25 \\ (-2.17) & (-0.70) & (-1.87) & (-0.71) & (-0.37) \\ 0.001 & -0.28 & 7.05 & -1.15 & -0.34 \\ (1.83) & (-2.60) & (2.02) & (-0.56) & (-0.47) \\ 0.00 & -0.00 & 0.20 & 0.13 & 0.01 \\ (0.58) & (-0.34) & (-2.29) & (2.44) & (3.09) \\ 0.00 & 0.01 & 0.19 & 0.39 & 0.01 \\ (1.20) & (1.56) & (1.25) & (4.33) & (2.15) \\ 0.00 & -0.30 & 0.39 & -4.49 & 0.94 \\ (1.36) & (-2.26) & (0.09) & (-1.74) & (3.20) \end{bmatrix} \cdot \begin{bmatrix} \Delta F_{t-1} \\ \Delta CP_{t-1} \\ \Delta I_{t-1} \\ \Delta P_{t-1} \\ \Delta SP_{t-1} \end{bmatrix}$$

$$+ \begin{bmatrix} -0.10 & 1.78 & 434.60 & -35.90 & -1.61 \\ (-1.75) & (0.25) & (1.47) & (-0.54) & (-0.81) \\ -0.00 & 0.02 & -7.98 & -1.46 & -0.03 \\ (-2.84) & (0.50) & (-4.26) & (-3.49) & (-2.51) \\ -0.00 & -0.00 & -0.22 & -0.03 & -0.00 \\ (-4.18) & (-1.11) & (-4.70) & (-2.70) & (-1.51) \\ -0.00 & 0.00 & -0.17 & -0.04 & -0.00 \\ (-3.03) & (0.16) & (-2.08) & (-2.41) & (-1.88) \\ 0.00 & 0.26 & 1.84 & -2.08 & -0.07 \\ (0.54) & (4.49) & (0.78) & (-3.93) & (-4.33) \end{bmatrix} \cdot \begin{bmatrix} F_{t-1} \\ CP_{t-1} \\ I_{t-1} \\ P_{t-1} \\ SP_{t-1} \end{bmatrix} . \quad (3)$$

A. Short-run and long-run Granger causality

In equation (3), the first term on the right hand side represents the constant, and the second term represents the short-run dynamics. From the second term, we see that the change in business failures is primarily caused by the change in business failures from the previous period. The changes in other variables do not have significant effects on changes in business failures, except that the effect of the interest rate is marginally significant. From another perspective, we also can see that the change in business failures has a marginally significant effect on corporate profits, but no significant effect on the other three variables.

The third term on the right hand side of equation (3) represents the long-run relationship among the five variables. More specifically, this term can be decomposed as $\Pi = \alpha\beta'$, where α is a N x r matrix and β is a r x N matrix, given that we have N (=5) variables and r (=3) cointegration vectors. a is usually interpreted as a loading matrix representing the speed of adjustment to deviations from the long-run equilibrium among the cointegrated variables, where β as contains the coefficients in the r cointegrating vectors. For variable p $(p = 1, \cdots, N)$ on the left hand side, its overall response to the long-run disequilibrium depends on the sum of its responses to all q $(q = 1, \cdots, 3)$ individual disequilibria via its loading coefficient α_{pq}. For example, the overall response of ΔF_t to the long-run disequilibrium may be written more specifically as $\alpha_{11} \cdot disequilibrium_1 + \alpha_{12} \cdot disequilibrium_2 + \alpha_{13} \cdot disequilibrium_3$, where $disequilibrium_q$ represents the amount of deviation from each of the three cointegration relationships. Each cointegration relationship is defined as $\beta_{q1} \cdot F_{t-1} + \beta_{q2} \cdot CP_{t-1} + \beta_{q3} \cdot I_{t-1} + \beta_{q4} \cdot P_{t-1} + + \beta_{q5} \cdot SP_{t-1}$. If all the α_{pq}s are zero, the variable would be called weakly exogenous, meaning that this variable p does not respond to any long-run disequilibrium. Such a hypothesis is tested for each of the variables in the system, and the results are summarized in Table 3. Among the five variables, at a 5 percent significance level, weak exogeneity is rejected for corporate profits, the interest rate, and the S&P 500 index. However, weak exogeneity cannot be rejected for business failures and is rejected only marginally for the producer price index, implying exogeneity of these two variables, especially business failures.

Table 3. Weak exogeneity test on loading matrix α

	Null hypothesis	Chi-sq	p-value
F	$\alpha_{11} = \alpha_{12} = \alpha_{13} = 0$	5.01	0.17
CP	$\alpha_{21} = \alpha_{22} = \alpha_{23} = 0$	16.69	0.00
I	$\alpha_{31} = \alpha_{32} = \alpha_{33} = 0$	18.81	0.00
P	$\alpha_{41} = \alpha_{42} = \alpha_{43} = 0$	8.23	0.04
SP	$\alpha_{51} = \alpha_{52} = \alpha_{53} = 0$	9.81	0.02

Note: F stands for aggregate business bankruptcies, CP for corporate profits, I for the interest rate, P for the producer price index, and SP for the S&P 500 stock price index.

Based on the above short-run dynamics and weak exogeneity test results (also called short-run and long-run Granger causality, respectively), we can see that business failures do not appear to be an endogenous variable determined by the other four variables. Instead, business failures seem to be comparatively exogenous among the five. Nevertheless, the interrelationship discussed thus far does not go beyond Granger-type causality (the lead-lag relationship). We subsequently consider contemporaneous causality and the interactions among the variables in time profiles given by innovation accounting.

B. Contemporaneous causal flows for identification

From the estimated VECM, the innovation correlation matrix is also obtained, as shown in Table 4. In this matrix (only the lower triangle is shown), the correlations between F and I, CP and SP, and P and SP are among the strongest. The remaining correlations are much weaker. This correlation matrix is used as a starting point for uncovering possible contemporaneous causality, to be represented as a DAG pattern. The matrix is processed by TETRAD (Scheines et al. 1994) without a priori knowledge of causality among the five variables.

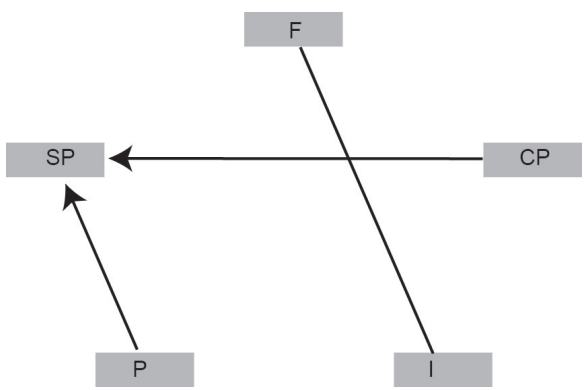
Table 4. Lower triangle of innovation correlation matrix

	F	CP	I	P	SP
F	1.000				
CP	0.028	1.000			
I	-0.264	-0.074	1.000		
P	-0.021	-0.063	0.089	1.000	
SP	-0.034	0.210	0.027	-0.234	1.000

Note: F stands for aggregate business bankruptcies, CP for corporate profits, I for the interest rate, P for the producer price index, and SP for the S&P 500 stock price index.

Using the PC algorithm, TETRAD proceeds with a complete set of undirected edges connecting each of the five variables to another. Edges are removed if a correlation or conditional correlation is not significantly different from zero for a given significance level. The remaining edges are directed by sepset conditions. The resulting directed graph, based on different levels of significance for the removal of edges, is given in Figure 2.

Figure 2. Directed graph pattern by PC algorithm



Note: Four significance levels (10, 20, 30, and 40 percent) are used and the results are the same across the four levels. F stands for aggregate business bankruptcies, CP for corporate profits, I for the interest rate, P for the producer price index, and SP for the S&P 500 stock price index.

Given the number of observations in this case, a significance level of 10 or 20 percent is appropriate (see the Monte Carlo results described in Spirtes, Glymour, and Scheines 2000). At either level, as shown in Figure 2, two directed edges are established. One directed edge shows a causal flow from CP to SP and the other is from P to SP. In addition, an edge exists between F and I, but it is not directed. For robustness, we go further to higher levels of 30 or even 40 percent (we understand that 30 percent is high by any hypothesis testing standards, yet it does allow us some idea of possible causal structures behind the data). Up to these levels, the DAG patterns are identical to those at the 10 and 20 percent levels.

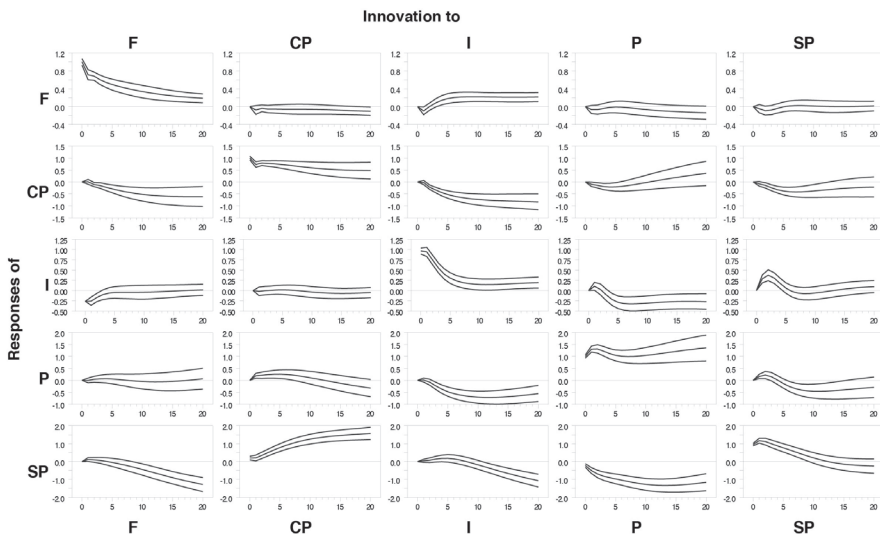
As for the undirected edge between F and I, insufficient information or a lack of true contemporaneous causality may be the reason for our inability to assign direction (this reason also explains the lack of direction between any two other variables). Given that we are unable to obtain a direction between F and I at usual significance levels, we test two alternative directions, namely, from F to I (directed by DAG at the 50 percent level) and from I to F. The following analysis results, impulse response function and forecast error variance decomposition, are shown to be almost identical between these two directions. The direction from F to I is chosen, given that it is the result supported by DAG, although at a higher significance level. This additionally directed edge and the two directed edges shown in Figure 2 define the contemporaneous causal structure to be used for VAR identification. For brevity, we may simply call this causal structure as the DAG-based causal structure in Figure 2 in the remainder of this paper.

C. Impulse response functions

The step from the DAG-based causal structure in Figure 2 to innovation accounting analysis follows the standard procedure in VAR. As in the case of Choleski and SVAR (Bernanke or Sims), the B_0 matrix (in Hamilton 1994, Chapter 11, notation) of contemporaneous relationship is first defined (restricted) based on the DAG contemporaneous causality and is used to estimate (identify) the underlying structural form of VAR model. With the structural model estimated (hence, the corresponding structural shocks), the innovation accounting analysis results are then computed.

Unlike the contemporaneous pattern revealed by the DAG, the impulse response functions presented in Figure 3 show the causal relationships over a horizon up to 20 quarters. The responses of all the five variables (normalized as each response is divided by the standard error of the corresponding innovation) to a one-time unit shock from itself or others, plus error bands, are shown in one of the 25 small graphs.[4] The variables undergoing shocks are listed on the top of the figure from column 1 to 5. The responses of the variables to each shock are shown in rows 1 to 5. We focus first on column 1 and row 1 to see how, in a qualitative sense, F influences other variables and how F is influenced by others.

Figure 3. Impulse response functions based on the causal structure in Figure 2



Note: F stands for aggregate business bankruptcies, CP for corporate profits, I for the interest rate, P for the producer price index, and SP for the S&P 500 stock price index. Each of the 25 small graphs in the figure represents the response of a variable to itself or another variable over a 20-quarter horizon. The responses of a variable to all variables (shown on the top of the figure) are shown in a single row from column 1 to 5. Alternatively, the responses of all the five variables to the same shock can be read in a single column from rows 1 to 5. For each response curve, the movement (response) of a variable has been normalized by dividing the response with the standard deviation of that variable.

[4] The error bands are likelihood-based bands as developed in Sims and Zha (1999) for overidentified SVAR. We use this method to provide a rough estimate for error bands in our structural VEC model.

In column 1, the response of CP to a shock in F is negative (a 2.7 percent drop)[5] and lasts over the 20-quarter horizon without dampening. SP responds negatively (with a 5 percent drop) to the shock in F, and the response becomes increasingly significant over time. Another variable affected by the F shock is I. I initially responds negatively (17 base points) to the F shock and is then back to normal roughly five quarters later. However, P basically does not respond to the F shock. While the effect from F to SP appears consistent with the firm-level failure phenomenon and is therefore easy to justify, the effects from F to CP and I appear more like a deviation from the group of studies started by Altman (1971, 1983). This deviation occurred because the effects of F on other variables are rarely addressed or simply assumed away from the beginning in the many studies since Altman (1971, 1983). Meanwhile, the effects found in this study are more in line with Liu (2009). Based on the flexible VAR framework that allows for mutual causality, Liu (2009) found that business failure rate exerts influence on all other five variables, namely, interest rate, credit, corporate profits, inflation, and business births. However, compared with Liu (2009), our result shows that the mutual influences between business failures and inflation are weak and so is the influence from business failures to interest rate.

The responses of F to the shocks from the other four variables are shown in row 1. A positive CP shock has a negative impact on F, but it is almost negligible in magnitude and does not appear to be statistically significant. The P and SP shocks have similarly negligible effects on F. However, F shows a positive response (a 1.5 percent increase) to I, and this response lasts into a long horizon. For this section of results, given that most previous studies focused on the effects of macro variables on business failures, a comparison of our results to theirs is easier to make. Among others, Altman (1983) found that reduced economic growth, negative stock market performance, and slower money supply all contribute to higher business failure propensity. In addition, Liu (2004, 2009) found that higher price level leads to a higher business failure rate via the channel of higher input cost and nominal interest rate. Compared with these studies, our results do not confirm any significant effect from CP, P, and SP. However, our result does show that a

[5] Other than the responses in terms of standard deviation shown in Figure 3, the numbers (in percentage or base point) in this bracket and in three other brackets are the translated values based on the estimated standard deviation and calculated sample averages for particular variables. For example, a 2.7 percent drop in CP is translated from a 0.6 standard deviation drop, given that one standard deviation in CP corresponds to 25.9 billion dollars, and the average CP over the sample period is 571 billion. These numbers are given particularly for the effects of F on CP, SP, and I and for the effect of I on F (covered in the immediately following paragraph) to offer a rough yet probably more realistic assessment.

higher interest rate results in more business failures. This finding lends support to some previous studies (Melicher and Hearth 1988; Liu 2004, 2009), indicating the importance of credit availability and cost to the survival of marginal firms, and further, the role of interest rate as a potential instrument when the control of bankruptcy risk is the policy target.

Although not the focus of this paper, the interactions among the other four variables can also be observed when we go through shock-delivering columns 2 to 5 and see their effects on rows 2 to 5. First, a shock to CP has limited effect on I, whereas this shock leads to a significant increase in SP, and a short-term increase in P followed by a decrease over time. Compared with CP, SP appears to be somewhat more influential. A shock to SP induces a negative response from CP to a certain degree, and positive responses from I and P in a short horizon that are followed by decreases over a longer horizon. Finally, a positive shock to I and P seems to have overall negative effects on all other variables, except that in response to a P shock, I first increases in a very short run (roughly two or three quarters) and then decreases afterwards.

D. Forecast error variance decomposition

Table 5 presents the forecast error variance decomposition results. Listed in the table for each variable (in one section) are six steps at 0 (contemporaneous time), 1, 2, 5, 10, and 20 quarters ahead. For each step, the entries show the percentage of variation in a variable that is due to innovations by itself and the other four variables. In addition to impulse response functions, forecast error variance decomposition offers an alternative way to look at the relative exogeneity (or endogeneity) of the variables more precisely.

Much like what we did with impulse response function results in the preceding subsection, we first examine the effects of the F shock on all variables by looking at column 1 (corresponding to F) across all five sections. First, a shock to F consistently explains significant proportions of its own variance across different horizons, as high as 81 percent even by the end of the 20-quarter horizon. Further, as to the effects on the other four variables, the F shock explains increasing proportions of CP variance (up to 19 percent) and SP variance (up to 12 percent) over the 20-quarter horizon. On the contrary, the effects of the F shock on I and P are limited. In the very short term (up to two quarters), 6 percent of I variance is attributed to F, and this drops roughly 4 percent in a longer horizon. The portion of P variance attributed to the F shock is even smaller and can be neglected.

Table 5. Forecast error variance decomposition based on the causal structure in Figure 2

Step	F	CP	I	P	SP
F					
0	100.0	0.0	0.0	0.0	0.0
1	98.7	0.3	0.6	0.3	0.1
2	98.4	0.3	0.4	0.4	0.5
5	96.3	0.5	2.3	0.3	0.6
10	90.8	0.8	7.5	0.5	0.5
20	80.7	1.8	14.3	2.7	0.4
CP					
0	0.0	100.0	0.0	0.0	0.0
1	0.0	99.0	0.0	0.6	0.4
2	0.5	94.9	2.1	1.3	1.2
5	3.2	75.1	12.3	3.0	6.4
10	10.1	52.6	25.3	2.0	10.0
20	18.6	34.2	36.7	3.0	7.5
I					
0	7.0	0.0	93.0	0.0	0.0
1	6.7	0.0	88.9	0.5	3.9
2	5.9	0.0	85.7	0.4	8.0
5	5.0	0.0	81.1	4.2	9.7
10	4.4	0.1	71.7	15.3	8.5
20	3.6	0.8	62.2	26.0	7.4
P					
0	0.0	0.0	0.0	100.0	0.0
1	0.0	1.3	0.0	97.7	1.0
2	0.0	1.8	0.1	96.4	1.6
5	0.1	3.0	4.6	91.0	1.3
10	0.1	2.6	14.5	77.7	5.1
20	0.1	2.1	17.9	73.8	6.2
SP					
0	0.0	3.9	0.0	4.9	91.2
1	0.5	3.0	0.1	11.3	85.2
2	0.5	4.5	0.2	17.1	77.7
5	0.3	14.0	0.9	29.7	55.2
10	1.9	30.1	0.6	39.8	27.6
20	12.3	37.3	7.2	33.9	9.3

Note: F stands for aggregate business bankruptcies, CP for corporate profits, I for the interest rate, P for the producer price index, and SP for the S&P 500 stock price index. Steps are in quarters. In each of the five sections, the decomposition results for each variable are shown at six selected steps from 0 (contemporaneous) to 20. For each step (in a row), the decompositions sum up to 100. Each component of the decompositions means the percentage of variance that is due to a variable itself or the other variables (shown in columns 1 to 5).

Next, we examine how F responds to shocks from itself and the other four variables by looking at columns 1 to 5 of the first section in Table 5. As before, each entry represents the variance decomposition at a particular moment, and the numbers across columns sum up to 100. Contemporaneously, 100 percent of F variance is attributed to itself. This is the case because F has been identified as a cause in contemporaneous time as established earlier by DAG. Over time, the effects of the other four variables kick in, and they explain varying yet largely growing percentages of the F variance. Particularly, the I shock is the most influential. By the 10th quarter, 8 percent of the F variance is attributed to the I shock, and the percentage rises to 14 by the 20th quarter. The effect of P is far more modest, followed by the negligible effects of CP and SP.

Overall, we can see that the patterns are consistent with what is shown by impulse response functions, that is, F can exert some influence on three other variables, CP, I, and SP, but it is not significantly influenced by the other variables, except I. Between F and I, the I shock is the primary reason for the F variance, other than its own shock. On the contrary, for I variance, the primary reason is the P shock, followed by SP, and then F. In other words, interest rate responds to a relatively wide set of factors, including inflation, stock market performance, and business failures, whereas business failures respond primarily to interest rate only, suggesting the relatively greater role of interest rate when compared with business failures.

V. Conclusion

Previous studies typically sought to determine the effect of macroeconomic conditions on aggregate business failures based on firm-level phenomena, implying an incomplete one-way causality. Arguing that business failures at the aggregate level should be modeled beyond our thinking about firm-level failure, i.e., the possible causality from business failures to macro conditions should be allowed, we have instead studied this issue in a cointegrated VAR built on DAG, a tool for data-driven causality identification. Based on such a data-driven framework, the interrelationship among aggregate business failures, aggregate corporate profits, interest rate, inflation, and stock market performance are examined for the case of the U.S. using quarterly data between 1980 and 2004, a period covered by the Bankruptcy Reform Act of 1978.

A central finding of our analysis is the exogeneity of aggregate business failures, i.e., aggregate business failures are not influenced much by other variables,

except that a positive shock to interest rate causes a lasting rise in business failures. Furthermore, a rise in business failures causes significant drops in corporate profits, stock market performance, and to a lesser degree, interest rate. This finding, especially the causal flows from business failures to macro variables, lends support to the mechanism proposed by Bernanke (1981), who showed that business failure risk can play a structural role in economic fluctuations. Based on that mechanism, rising bankruptcy risk makes all agents in the economy cautious. As a result, consumers and firms cut or defer their purchasing, whereas lenders become more selective and limit the size of their loans, which, in turn, deepens a recession.

In a broader view, the results in this study relate to the wider scope of literature regarding the effect of corporate financial conditions on macroeconomic conditions (e.g., Fazzari, Hubbard, and Petersen 1988, Carpenter, Fazzari, and Petersen 1994, Gilchrist and Himmelberg 1995, among others). Particularly, as summarized in Bernanke, Gertler, and Gilchrist (1998), from a perspective that gives a central role to credit market conditions in economic fluctuations, "deteriorating credit-market conditions – sharp increases in insolvencies and bankruptcies, rising real debt burdens, collapsing asset prices, and bank failures – are not simply passive reflections of a declining real economy, but are in themselves a major factor depressing economic activity." To our knowledge, few previous studies contain direct evidence for the causal effect from business failures to economic fluctuations. The result documented in this work, along with that in Liu (2009), may be viewed as supplying such evidence confirming the proactive role of bankruptcies. In this perspective, the policy implication of our findings goes beyond business failures. It actually takes us back to the general story regarding the role of monetary policy as a credit policy in stabilizing the economy. Such a general context should be the policy background against which policy makers think about the best responses to business failure risk in the use of monetary instruments.

References

Altman, Edward I. (1971), *Corporate bankruptcy in America*, Lexington, MA, Heath Lexington Books.

Altman, Edward I. (1983), Why businesses fail, *Journal of Business Strategy* **3**: 15-21.

Awokuse, Titus O., and David A. Bessler (2003), Vector autoregressions, policy analysis, and directed acyclic graphs: An application to the U.S. economy, *Journal of Applied Economics* **6**:1-24.

Bernanke, Ben S. (1981), Bankruptcy, liquidity, and recession, *American Economic Review* **71**: 155-9.

Bernanke, Ben S. (1986), Alternative explanations of the money-income correlation, *Carnegie-Rochester Conference Series on Public Policy* **25**: 49-100.

Bernanke, Ben, Mark Gertler, and Simon Gilchrist (1998), The financial accelerator in a quantitative business cycle framework, Working Paper 6455, NBER.

Bessler, David A., and Jian Yang (2003), The structure of interdependence in international stock markets, *Journal of International Money and Finance* **22**: 261-87.

Carpenter, Robert E., Steven M. Fazzari, and Bruce C. Petersen (1994), Inventory investment, internal finance fluctuations, and the business cycle, *Brookings Papers on Economic Activity* **2**: 75-122.

Chava, Sudheer, and Robert A. Jarrow (2004), Bankruptcy prediction with industry effects, *Review of Finance* **8:** 537-69.

Demiralp, Selva, and Kevin D. Hoover (2003), Searching for the causal structure of a vector autoregression, *Oxford Bulletin of Economics and Statistics* **65**: 745-67.

Fazzari, Steven M., R. Glenn Hubbard, and Bruce C. Petersen (1988), Financing constraints and corporate investment, *Brookings Papers on Economic Activity* **1**: 141-95.

Gilchrist, Simon, and Charles P. Himmelberg (1995), Evidence on the role of cash flow for investment, *Journal of Monetary Economics* **36**: 541-72.

Hamilton, James D. (1994), *Time series analysis*, Princeton, NJ, Princeton University Press.

Hansen, Henrik, and Katarina Juselius (1995), CATS in RATS: Cointegration analysis of time series, Evanston, IL, Estima.

Hudson, John (1986), An analysis of company liquidations, *Applied Economics* **18**: 219-35.

Johansen, Soren (1991), Estimation and hypothesis testing of cointegration vectors in Gaussian vector autoregressive models, *Econometrica* **59**: 1551- 80.

Liu, Jia (2004), Macroeconomic determinants of corporate failures: evidence from the UK, *Applied Economics* **36**: 939- 45.

Liu, Jia (2009), Business failures and macroeconomic factors in the UK, *Bulletin of Economic Research* **61**: 47-72.

Melicher Ronald W., and Douglas Hearth (1988), A time series analysis of aggregate business failure activity and credit conditions, *Journal of Economics and Business* **40:** 319- 33.

Pearl, Judea (1986), Fusion, propagation, and structuring in belief networks, *Artificial Intelligence* **29**: 241- 88

Platt, Harlan D., and Marjorie B. Platt (1994), Business cycle effects on state corporate failure rates, *Journal of Economics and Business* **46**: 113- 27.

Rose, Peter S., Wesley T. Andrews, and Gary A. Giroux (1982), Predicting business failure: a macroeconomic perspective, *Journal of Accounting, Auditing, & Finance* **6**: 20-31.

Scheines, Richard, Peter Spirtes, Clark Glymour, and Christopher Meek (1994), *TETRAD II: user's manual and softwar*e, New Jersey, NJ, Lawrence Erlbaum Associates, Inc.

Sims, Christopher A. (1980), Macroeconomics and reality, *Econometrica* **48**: 1-48.

Sims, Christopher A. (1986), Are forecasting models usable for policy analysis?, *Federal Reserve Bank of Minneapolis Quarterly Review* **10**: 2-16.

Sims, Christopher A. and Tao Zha (1999), Error bands for impulse responses, *Econometrica* **67**: 1113-55.

Spirtes, Peter, Clark Glymour, and Richard Scheines (2000), *Causation, prediction, and search*, Cambridge, MA, MIT Press.

Swanson, Norman R., and Clive W.J. Granger (1997), Impulse response functions based on a causal approach to residual orthogonalization in Vector Autoregression, *Journal of the American Statistical Association* **92**: 357-67.

Wadhwani, Sushil B. (1986), Inflation, bankruptcy, default premia and the stock market, *Economic Journal* **96**: 120-38.