FABIO CANOVA

Were Financial Crises Predictable?

THIS PAPER EMPIRICALLY INVESTIGATES the nature of financial crises in the United States in the pre-World War I era in an attempt to shed light on their informational characteristics and on their generating mechanisms. In particular, the paper addresses the questions of (1) whether there are variables that reveal conditions conducive to crises, (2) whether financial crises were forecastable on the basis of the information set available to agents, and (3) whether they were alike, in the sense that a set of statistical relationships was common to all episodes.

There are several reasons to address these questions at an empirical level. First, early literature on the subject has suggested that movements in interest rates, in stock returns and in changes in the deposit to currency ratio are key factors in understanding the occurrence of crises (see, for example, Friedman and Schwartz 1963, Kindleberger 1978, and Minsky 1977). However, surprisingly little statistical work has been expended to document the significance of these variables in revealing the conditions conducive to crises. Two exceptions are Bordo (1985) and Gorton (1989). Second, although before 1914, banking panics occurred almost simultaneously with financial crises and stock market crashes, the current literature on banking panics (see, for example, Diamond and Dybvig 1983, Jacklin 1987, Waldo 1985, Chari and Jagannathan 1988, and Williamson 1989) has failed to spell out their implications for financial markets. An empirical analysis of the generation mechanism of financial crises may shed some light on these links and on the causal relationship between banking panics and financial crises [see Wilson, Sylla, and

The author thanks Glen Donaldson, Peter Garber, Pat Hess, Bong Soo Lee, Jane Marrinan, Jeffrey Miron, and, especially, Chris Sims for comments, and two anonymous referees for helpful suggestions.

FABIO CANOVA *is associate professor of economics at Brown University.*

Journal of Money, Credit, and Banking, Vol. 26, No. 1 (February 1994)

Jones (1990) for an attempt in this direction]. Third, although crises have been described as "unsettling but not especially surprising, they were expected to happen every so often; the real question was when" (Wilson, Sylla, and Jones 1990), the question of the predictability of financial crises has never been explicitly investigated. One reason for the lack of empirical work in this area is that in most recent theories panics are generated through sequential liquidity constraints and self-fulfilling expectations. Therefore they offer little guidance on the choice of leading indicators for crises and impose very weak restrictions on the joint behavior of macroeconomic and financial variables both before and during crisis periods.

The questions of the significance of certain variables in revealing conditions conducive to crises and of the predictability of financial crises are important because past experience may help us understand the 1987 stock market crash and the recent savings-and-loans crisis and indicate whether agents could have avoided wealth losses using selected variables and simple forecasting rules.

Since the earlier literature on financial crises pointed out their tendency to occur in seasons when the money market was tight (see, for example, Jevons 1884, Palgrave Inglis 1910, Sprague 1910) or at the peak of the business cycle (see, for example, Mitchell 1913, Fisher 1933, or Minsky 1977), one forecasting device is a model including simple seasonal or cyclical indicators. This model can also provide formal evidence on the long-standing, but never formally tested belief that financial crises had a recurrent and/or quasi-periodic nature (see, for example, Miron 1986).

In addition to models including seasonal and cyclical indicators the paper examines the performance of several other theory-based forecasting specifications. Contrary to existing work in the area (see, for example, Calomiris and Gorton 1991), the paper uses out-of-sample criteria to compare the forecasting ability of various specifications and to judge the relevance of results. The conclusions of the paper are as follows: there are variables that are significant in explaining the economic conditions conducive to crises (the money supply, the volume of excess cash reserves of New York banks, stock returns, and the volatilities of stock returns and of the domestic interest rate spread). In addition, I find that the probability of crises is explained by seasonal indicators but that business cycle events have little effects on the probability of crises. Despite these in-sample findings, the out-of-sample forecasting ability of all the models examined is poor. The only exception is a model that uses volatility measures of financial aggregates as independent variables which predicts the occurrence of two crises (1884 and 1901) with 50 percent or more probability. Finally, since different crises had different degrees of predictability, the results also suggest that crises were not all statistically alike and that their generation mechanisms differed.

The paper is organized in five sections. The next section presents a brief historical account of the events, the hypotheses concerning the trigger mechanisms for crises and a list of variables that theories have suggested as leading indicators for financial crises. Section 2 describes the data. Section 3 presents the definition of a crisis and discusses alternative definitions existing in the literature. Section 4 introduces the econometric techniques and discusses the results. Conclusions appear in section 5.

1. SOME HISTORICAL EVIDENCE AND THE HYPOTHESES

During the National Banking Era several financial crises occurred in the United States. All episodes were characterized by skyrocketing interest rates, a precipitous decline in asset prices, increased bankruptcy and insolvency rates, substantial drops in the total stock of money in circulation, and a breakdown of the allocation mechanism of financial capital.

Several hypotheses have been advanced to explain this recurrent pattern of events. The most popular explanation in the earliest literature focused on the seasonal cycle in agriculture in conjunction with the pyramidal structure of bank reserves during the National Banking era and the absence of a lender of last resort (and the consequent inelastic supply of currency in the short run) (see, for example, Kemmerer 1910, Andrew 1907). The chain leading to a crisis was typically thought to start when some event caused agents to demand liquidity in excess of their normal cash flow. As depositors pressured illiquid local banks, these rural intermediaries withdrew reserve funds from city banks and New York reserve banks, who in turn called in outstanding loans, liquidated marketable assets or borrowed from abroad. Stock market brokers, whose loans were called in, sold their collateralized securities in the market, usually for a loss, or attempted to obtain cash from domestic and foreign sources. These effects combined to generate situations of acute financial stringency in the money market which, every so often, degenerated into crises.

The economy was thought to be more prone to crises at planting and harvesting times when the money market was seasonally stringent. Since the supply of currency was inelastic in the short run, unusually strong seasonal pressure in the money market made stock market crashes and bank runs more likely to happen. Chari (1989) attempts to provide a link between this "seasonal" approach and modern theory of banking panics a la Diamond and Dybvig by identifying exceptional seasonal demand for currency as the mechanism triggering self-fulfilling bank runs. This explanation of the historical facts also predicted that the recurrent pattern would disappear if liquidity shortages were eliminated. Many authors have credited the Fed with alleviating the probability of crises by inducing seasonal elasticity in monetary aggregates [Miron (1986) and Barro (1989) are the most recent examples; see Clark (1986) for an opposite view].

Sprague (1910) and Dewald (1972) accept the chain of events previously described but point to the unwillingness of New York banks to perform Central Bank functions as the primary catalyst for crises. Using approximate rules of thumb, New York banks often stopped paying out cash whenever their reserves fells below 25 percent of their liabilities. This fraction, which was set as an approximate target by the Clearing House Association, was well above any European Central Bank standard and was viewed by banks and the public as an irreducible minimum, not a resource to be used for emergencies (see Sprague, p. 135). It was this conservative attitude of New York banks, rather than an unexpectedly high demand of funds from farming regions, that was thought to be primarily responsible for precipitating situations of monetary stringencies into crises and runs.

Jevons (1884, p. 8) presents a related but independent argument. He claims that unexpected events occurring in conjunction with a predictable seasonal pattern in financial variables strained the system to such an extent that public confidence in the banking system waned. This argument seems particularly well suited to explain the European and Canadian experiences where the presence of a Central Bank providing a seasonally elastic supply of currency was not sufficient to prevent the explosion of financial crises. Canova (1991) shows that Jevons' hypothesis also has some merit in accounting for crises in the United States. I find that unexpected changes in the world arena often produced a disruption of the regular (seasonal) flow of specie and credits to the United States from Europe and that these disruptions preceded by a few months and were statistically prior to the explosion of many crises. I interpret the decreased occurrence of financial crises in the post-1914 era as the result of the Fed standing ready to provide liquidity to the system at times when international markets failed to do so.

Several other authors (see, for example, Juglar and Thom 1915, Morgenstern 1959, and Bordo 1985) also noted the tendency of financial crises to have an international dimension with many crises in the United States preceded by very stringent money market conditions or crises in Europe. In addition, Sprague, Friedman and Schwartz, and Lauck (1907) have pointed out that foreign sales of American securities and increases in the discount rate charged by the Bank of England both played crucial roles in inducing abnormal gold outflows immediately prior to the 1890, 1893, 1907, and 1914 crises. Although each crisis had its country-specific features, international interest rate parity failed to hold in the months preceding the explosion of a crisis in the United States.

A second theory, developed in the works of Mitchell (1913), Fisher (1933), Minsky (1977), and Kindleberger (1978), views financial crises as endogenous to the economic process and sees them appearing at the peak of the expansion phase of the business cycle. According to this theory, the financial environment becomes fragile toward the end of a business cycle expansion because firms have difficulties meeting their debt payment commitment as a result of a decline in business profits (see Mitchell 1913, pp. 39–48); firms rely on debt to finance capital investments and on speculative schemes to increase expected profits; and there exist excessively optimistic expectations about the future of the economy (see, for example, Minsky 1977, pp. 139–46).

The firms' increased demand for funds to meet payments on debts is typically met by an increase in the outstanding amount of commercial loans. A crisis explodes when the deterioration of the financial position of several firms and their reduced outlook for future profitability cause creditors to reevaluate the amount of credit to be issued, to refuse to extend additional credit and, in the extreme, to actively seek the liquidation of existing outstanding loans. The inability of firms to refinance debt forces them to liquidate assets and induces a multiplicative contraction in business profits. When this distress selling is widespread, asset markets crash and bankruptcies ensue.

Early proponents of this theory all indicate the presence of a psychological element associated with financial crises (a sudden panic developing from the scramble for liquidity) but they do not agree on its timing. For example, Mitchell sees a panic arising when the process of liquidation of outstanding credit reaches weak links of the system and the bankruptcy of large enterprises spreads unreasonable alarm. Minsky sees a panic appearing after asset prices have sharply dropped. Others identify the scramble with the intense demand for money to meet payments arising from an abrupt cessation of credit. All authors, however, seem to concur that the abnormal decrease in bank deposits associated with a run follows the appearance of a crisis rather than precedes it.

The process of learning about a shift in the underlying distribution of possible outcomes repeatedly appeared in early writings (see New York Press (1857, p. 1), and Thom and Thom (1915, p. 2)), and is at the heart of the explanation of crises provided in Meltzer (1982) and by the modern asymmetric information theory of panics (see, for example, Calomiris and Gorton 1991). The basic idea of the latter (see, for example, Chari and Jagannathan 1988 or Gorton 1989) is that in an environment with asymmetric information, a particular class of agents (bank depositors or banks themselves) may receive information leading them to reassess the risk of their investments without knowing which particular economic unit is most likely to be affected by the news. A phase of credit crunch by banks serves the positive effect of their monitoring firm managers to sort out who is insolvent and who is not. Similarly, a banking panic serves to monitor bank performance when banks are involved in the production of nonmarketable assets which are difficult to value. In both cases, the rational revision of beliefs occurs after new information accrues to agents in the economy. However, since only negative shocks are likely to start this revision process, implicit in this hypothesis is the idea that agents react asymmetrically over the business cycle making credit crunches (or bank panics) more likely to occur around the end of an expansion or the beginning of a contraction.

The third theory presented by Friedman and Schwartz (1963, p. 311) and Cagan (1960, p. 226) emphasizes the role of contractions in the money stock in triggering a forced liquidation of assets by commercial banks. They claim that runs on banks and the inability to expand the stock of money sufficiently to compensate for the drop in bank reserves greatly intensified contractions and set off crises. The nonbanking public's switch from deposits to currency was thought to be the result of either a prior contraction in the money stock or of a change in the public's confidence in banks' ability to convert deposits into currency.[1] The forced liquidations of banks' assets produced severe drops in asset prices, raised interest rates, and threatened banks' solvency. When this process was accompanied by the failure of prominent financial institutions or railroads, confidence plunged even further transforming a stringency into a crisis. Since the volume of deposits converted into currency and the demand for liquidity was large especially at planting and harvesting times and when (negative) shocks changed the perception of the riskiness of bank deposits, this theory also implies that financial crises were more likely to occur during the

1. Although it is never explicit in the work of Friedman and Schwartz, Calomiris and Gorton (1991) suggest that real shocks may be the cause of the erosion of public's trust in the banking system.

agricultural cycle and during business cycle contractions. However, contrary to the previous two explanations, this theory attributes a special causal role to banking panics in the generation of financial crises.

Finally, a recent hypothesis proposed by Wilson, Sylla, and Jones (1990) and partially examined by Schwert (1989) suggests a connection between stock market volatility and crises where stock market crashes precede and induce banking panics and recessions. Their line of argument is that because of a bubble, volatility in the stock market is higher than normal and the demand for credit to finance stock speculation soars, pushing short-term interest rates up. Stock speculation is unrelated to fundamentals and builds its momentum in the steady rise of stock prices. When the bubble bursts or runs against other constraints and when the insolvency of those banks that finance the speculation becomes publicly known, the call rate skyrockets, security prices tumble and banks are run. Thus, it is the breakdown of the allocation mechanism of financial capital that causes contractions in business activities and leads to a recession.

Each of the four theories presented has implications for the timing of the occurrence of a crisis. According to the seasonal-based theory of crises, the probability of a crisis was high either (i) when the number of bank clearings was seasonally high or the level of excess reserves relative to the 25 percent boundary in New York banks was seasonally low, or (ii) when unexpected shocks (domestic or international) occurred in conjunction with a regular seasonal drain of currency out of New York. An indicator of unexpected shocks in the system is the size of unexpected declines in excess reserves of New York banks. An indicator of the importance of international factors in generating domestic crises is the spread between short-term interest rates in the United States and in England. A large negative excess reserve shock or a large negative spread at times when seasonal demand for currency was high would make crises more likely to occur.

The credit-business cycle theory, on the other hand, suggests that a high degree of leverage combined with low business profits or a large spread between domestic short-term and long-term interest rates should unveil a situation when the probability of crises was high. In its modern version it suggests that cyclical indicators should help to discern when crises are more likely to occur. The monetary theory of crises predicts that contractions (both expected and unexpected) in the money stock as well as unexpected drops in the deposit-to-currency (D/C) ratio reveal economic conditions conducive to crises. Finally, the bubble theory of crises indicates that abnormal volatility in stock returns occurring in conjunction with high volatility in the spread between short-term and long-term interest rates is a leading indicator for situations of high probability of crises.

Since all these variables belonged to agents' information set, they should have been able to determine when the probability of crises was high. In addition, those hypotheses that indicate that crises are more likely to occur during a particular phase of the seasonal or the business cycle suggest that a high probability of crisis must be predictable on the basis of seasonal or cyclical indicators. Finally, if the same generating mechanism was at work in each episode, no crisis should be better predicted than the others using the available information. The rest of the paper is devoted to verifying all these conjectures.

2. THE DATA

The data available for the National Banking Era (1864–1914) is heterogeneous and less than satisfactory in several respects. First, most financial series measure monthly averages, or averages over the last week of the month or even averages of the high and low for a month. This creates aggregation problems similar to those discussed by Working (1960). Second, the monetary aggregates reported in the traditional sources undergo substantial definitional changes over the period under consideration. Third, many variables that could be used to gauge the state of "fundamentals" or of the business cycle are available only at a quarterly or yearly frequency (for example, the business failure series). Therefore, determining the merits of the credit-business cycle theory, in particular, requires the use of debatable proxy indicators.

I have compiled monthly series, attempting to assemble the highest quality data available under the same definition. I chose a monthly frequency for two reasons. First, monthly data are continuously available for the 1880–1914 period. Second, a month is not too large a time span when compared with the length of a typical crisis. Also, because the quality of the data deteriorates substantially before 1880, I decided to concentrate the analysis on the 1880–1914 period.

U.S. interest rate data is taken from Macaulay (1938) and measures monthly averages of daily figures. The call money rate is the renewal rate at the NYSE desk and refers to loans made for an indefinite period of time subject to recalls with twenty-four-hours notice and requiring collateral to be deposited at the bank issuing the loan. Since renewal rates tend to be less volatile than the new rates, this series is not necessarily a good indicator of the true market conditions. The bond rate measures monthly averages of daily rates for an index of high-quality debt instruments with maturities of twenty years or more. The bonds included in the index and their maturities vary over time but the high quality of the instruments remains throughout the sample. The commercial paper rate is the average rate on "choice 60–90-day two-name paper" and pertains to high quality short-term promissory notes.[2] Data on pig iron production, used here as a proxy for cyclical indicators, also comes from Macaulay and measures daily averages in thousands of gross tons.

There are several sources for stock price data. Macaulay provides monthly averages of daily figures for the index number of the prices of railroad stocks weighted by the number of shares outstanding at the beginning of the year. However, the stock market data he reports for the period 1914,8–1914,11 is dubious because the stock market was closed during that period. Cowles (1939) provides a monthly average of the high and low of a value-weighted index of the prices of *all* stocks actively traded on the New York Stock Exchange and monthly averages of value-weighted

2. The commercial rate is not very indicative of the conditions existing during crises because that market was completely inactive when crises occurred. However, the flattening or the reversal of the yield curve in the months preceding a crisis may have provided useful information.

sectorial price indices (including railroad, industrial, and steel stocks). Finally, Dow Jones provides a daily price-weighted index of stock prices from 1889 to 1915. Data from 1889 to 1895 includes eighteen railroads and two industrial stocks, while data after 1895 reports the average price of twenty railroad stocks. I sampled Dow Jones data at the end of the month to construct the corresponding monthly series. Dow Jones also provides a daily series on the trading volume of the New York Stock Exchange. However, since this series starts only in 1897, it cannot be used to gauge the volatility of the market in the earlier periods.

Additional information on the performance of individual stocks included in various indices and on the state of fundamentals in the economy is hard to obtain. Price-earning ratios, dividends, and profits of the firms are available only at a yearly frequency. The only indicators of the profitability of firms that are available at a monthly frequency are the "Yield Expectations" series constructed by Cowles. These series measure the expected annual income (estimated each month) per dollar of security value for various market portfolios. The expected annual income is computed as the product of the quantity of stock outstanding and four times the quarterly rate last declared, unless the corporation announced that a change in the rate was going to be made or extra dividends were going to be paid, in which case the rate was adjusted accordingly.

Time series for useful banking variables can also be found in Macaulay. He reports the daily averages of the number of bank clearings in and outside New York City. To construct time series for the end-of-the-month amount of vault cash, deposits, loans and discounts of New York banks I resorted to issues of *The Commercial and Financial Chronicle* and of *The Banker's Magazine*.

Averages over the month of high-powered money (HPM) in circulation are taken from various issues of the *Reports to the Comptroller of the Currency* and integrated, when missing, with those appearing in Andrew (1910). The HPM series used here measures the amount of currency in circulation and includes gold coins and certificates, silver coins and certificates, Treasury and U.S. notes, currency certificates, and subsidiary silver outside the Treasury.

Since data for the U.K. call rate is available only for the period 1889–1908, the foreign interest rate series used here is a mixture of the call money rate (1889–1908) and of the market rate for overnight loans charged by discount brokers' banks in London (1909–1914). The bias introduced in the late part of the sample by this splicing procedure is likely to be small in practice because both rates are of a very short-term nature and both are used in financing callable loans. The sources of the data are Palgrave Inglis (1910) up to 1908 and Goodhart (1972) afterwards. Since the data refer to the quoted rate at the first Friday of each month, I lagged the series one period to construct a measure of international interest rate spread.

3. A DEFINITION OF CRISIS

A crucial step in examining the questions posed in the introduction is the provision of an appropriate definition of a crisis and the construction of a reasonable time series characterizing the events. Although there seems to be a broad consensus on the general features of crises, interested authors have emphasized different aspects of the phenomena. Mitchell (1913), for example, defines financial crises as the process of intense liquidation of credit. For Friedman and Schwartz (1963) a financial crisis is a situation where banks are forced to sell assets at a loss to replenish reserves; for Fisher (1933) and Minsky (1977) a financial crisis is a sharp decline in stock prices following the forced sale of assets by overindebted firms; for Sprague (1910) and Dewald (1972) a crisis is identified with the suspension of the convertibility of deposits into currency. In general there need not be any coincidence between these various phenomena, but for the pre-1914 experience in the United States stock market crashes and liquidity crunches all occurred simultaneously with bank runs and in some of these episodes convertibility was suspended. Therefore, by adopting Jevons' (1884, p. 8) definition of crisis as "a rapid rise in the rate of discount, a sudden flood of bankruptcies, and a fall in consols [prices], followed by a rise," we cover the largest possible set of occurrences when abnormal disturbances hit financial markets.[3] According to this definition, the U.S. economy experienced eight crises for the 1880–1914 period, approximately one every four years. The starting dates for these events differ depending on the source. Kemmerer (1910) reports 1884,6; 1890,9; 1893,5; 1899,12; 1901,5; 1903,3; 1907,10 (plus 1914,8). Friedman and Schwartz have a slightly different chronology with the first three crises starting a month before or after Kemmerer's.

There are two reasons for these chronological differences. First, some crises lasted more than a month and the literature disagrees on the events precipitating crises. Second, some crises occurred between two months and it is difficult to pin down the starting date. To avoid spurious results due to a misspecification of starting dates, I generate two dummy series and examine the evidence with each of them. In the first (denoted by y_{1t}), I assign a one to the month when a crisis starts according to the earliest data reported and a zero otherwise. In the other (denoted by y_{2t}), I assign a one to the months when a crises was in progress and a zero otherwise. The two series differ primarily in the 1907 and 1914 episodes, since these crises lasted three and five months, respectively.

There is also some disagreement on which episode should really be considered a crisis. Sprague (1910), for example, lists only the 1893, the 1907, and the 1914 episodes as crises and catalogs the others as minor panics. Schwert (1989) adds the stringency of 1896,12 to the above list of crises. Even though a threat of bank runs developed (see Sprague 1910), no unusual event actually disturbed the functioning of financial and money markets at this date. Finally, Gorton (1989), Calomiris and Gorton (1991), and others have concentrated attention on those crises where the convertibility of deposits into currency was suspended (that is, 1884, 1890, 1893, 1907) or threatened (1896). While this could be appropriate in testing theories of banking panics, it is somewhat restrictive here. Banking panics and the associated

3. This definition of a crisis is recurrent in the early chronicles and in current work on financial crises (see, for example, Lauck 1907, Juglar and Thom 1915, and Eichengreen and Portes 1987).

suspension of convertibility are important components of financial crises, but they are neither the sole determinant nor the unique object of an analysis designed to predict periods of turmoil in financial markets. However, it turns out that none of the results I present here depends on which taxonomy is used. Therefore the selection of which episode is a relatively minor issue when compared with the choice of starting dates.

4. THE ECONOMETRIC PROCEDURE AND THE RESULTS

To examine the predictability of crises I evaluate the performance of probit models of the form:

$$Pr(y_{it} = 1|x_t, \beta_t) = F(x_t, \beta_t)$$

where x_t is a set of explanatory variables belonging to the information set of agents at t-1, β_t is a vector of free parameters to be estimated, F is the cumulative normal distribution function and y_{it} is the dummy crisis series, $i = 1{,}2$; $0 \leq t \leq T$. Estimates for the β_is are found by recursively maximizing the log likelihood function

$$L_t = \sum_{\{y_{ij}=1, j\leq t\}} F(x_j\beta_j) + \sum_{\{y_{ij}=0, j\leq t\}} [1 - F(x_j\beta_j)] \tag{1}$$

for each t. Recursive estimates are used here because they mimic the estimates that agents could have obtained at each t if the probit technique were available to them. The "in-sample" fit of each model is formally assessed with a Wald test for the joint significance of all the coefficients. Their forecasting ability is evaluated using six statistics (Brier quadratic probability score (QPS), a global calibration statistic (GBS), the average likelihood statistic (AL), the number of incorrect cases (INCORRECT), and type I and II errors and a plot of the estimated recursive probability of the event that actually occurred, that is, a plot of $w_{it} = Pr[y_{it} = \bar{y}_{it}|x_t\widehat{\beta_t}]$, $i = 1{,}2$; $0 \leq t \leq T$, where $\hat{\beta}_t$s are the recursive maximizers of (1) and $\bar{y}_{it}$ is either a zero or a one.

The QPS and GBS statistics that have been used in the literature on scoring leading indicators [see, for example, Diebold and Rudebush (1989)] measure, respectively, the closeness, on average, of predicted probabilities and actual realizations and the overall closeness of forecast probabilities and observed relative frequencies. They are given by $QPS = \frac{2}{T}\Sigma_{t=1}^{T} (P_t - R_t)^2$; $GBS = 2(\bar{P} - \bar{R})^2$ where P_t is the probability forecast of a crisis, R_t is the actual realization, and $\bar{P}$ and $\bar{R}$ are their unconditional means. The two statistics are bounded between zero and two with a zero corresponding to a streak of perfect forecasts.

The AL statistics is given by $AL = \frac{T}{2}\log\left(\frac{1}{T}\Sigma_{t=1}^{T}\frac{\hat{v}_t^2}{v_t/v}\right)$ where $\hat{v}_t = y_t -$

$\hat{E}(y_t|x_t, \beta_t)$, $\hat{E}$ is an estimator of the conditional expectation, $v_t = var(y_t)$ and v is the geometric average of v_t, measures the (geometric) average predictive probability of the model and is bounded between 0 and 1.

The number of incorrect cases reports how many times the model fails to predict with at least 50 percent probability the events that actually occur. Therefore it roughly measures the performance of the models when a 50 percent cut-off probability rule is used. A concentration of incorrect cases at crisis dates indicates a substantial failure of the model.

The last two statistics (Type I and II errors) measure, respectively and on average, probability of a crisis not occurring when it actually did occur (average conditional probability of missing the signal) and the probability of a crisis occurring when a crisis did not occur (average conditional probability of a false alarm). Finally, the plots of recursive probability have a simple and intuitive interpretation: if the model forecasts appropriately, the time series plotted should always be close to 1. A value close to zero at some t indicates the presence of an event not captured by the model (outlier). A clustering of outliers at crisis dates suggest that the model is poor in forecasting crises.

Table I reports the results obtained with the "best" model specification for each of the four theories.[4] In model 1, which reports the results for the agricultural-seasonal hypothesis, x_t includes a constant and three lags of the spread between the United States and the United Kingdom call rate (Spread2), of the excess cash reserves of New York banks (relative to the 25 percent level) (Excash), and of the unexpected number of clearings in New York (ClearNY). In model 2, which reports the results for the credit-business cycle hypothesis, x_t includes a constant and three lags of the spread between the bond and the commercial rate (Spread1), of the level of excess loans of New York banks relative to their trend (Loans), and of returns on a value-weighted portfolio of railroad securities (Return). The first two variables proxy for overindebtness and the last one for expected business profits. Model 3, which reports the results for the monetarist theory, includes as explanatory variables a constant, three lags of unexpected movements in the money supply (Money), and three lags of unexpected movements in the deposit to currency ratio (DC). Unexpected movements are constructed by taking the residuals of univariate AR(13) regressions. In model 4, which reports the results for the bubble hypothesis, x_t includes a constant, three lags of the volatility of the spread between the bond and the call rate (VolSP), of the volatility of returns on a value-weight portfolio of railroad stocks (VolRet), and of the trading volume in the New York Stock Exchange (Volume). Recursive measures of volatility are computed as the absolute value of the residuals of a recursive autoregression of the variable under consideration on thirteen lags and twelve seasonal dummies [as in Schwert (1989)]. Finally, model 5 presents the performance of a "naive" forecasting model, that is, a model which assigns a zero probability to a crisis event at all t. This model, which is the analog of a random

4. Several combinations of variables were tried in order to determine the best model specification for each theory and to examine the robustness of the conclusions. The estimation results from all these specifications are available on request from the author.

TABLE 1

RECURSIVE PROBIT ESTIMATION SAMPLE 1881,4–1914,12

	Crises 1							
Constant	−1.680	(−4.40)						
Spread2(−1)	−0.040	(−0.40)						
Spread2(−2)	0.010	(0.15)						
Spread2(−3)	0.010	(0.23)						
Excash(−1)	−0.010	(−0.91)						
Excash(−2)	−0.001	(−0.08)						
Excash(−3)	−0.005	(−0.35)						
ClearNY(−1)	−0.8E-7	(−0.10)						
ClearNY(−2)	0.7E-5	(0.95)						
ClearNY(−3)	−0.4E-5	(−0.54)						
Constant			−2.350	(−9.83)				
Return(−1)			−0.002	(−0.95)				
Return(−2)			−0.003	(−0.78)				
Return(−3)			0.008	(2.30)*				
Loans(−1)			−0.008	(−1.23)				
Loans(−2)			0.003	(0.31)				
Loans(−3)			0.004	(0.61)				
Spread1(−1)			0.229	(0.71)				
Spread1(−2)			−0.449	(−1.00)				
Spread1(−3)			0.092	(0.28)				
Constant					−2.350	(−10.69)		
Money(−1)					−0.009	(−1.39)		
Money(−2)					−0.014	(−2.20)*		
Money(−3)					−0.002	(−0.42)		
DC(−1)					−16.60	(−1.17)		
DC(−2)					−24.43	(−1.69)		
DC(−3)					8.91	(0.79)		
Constant							−2.023	(−4.63)
VolSP(−1)							0.211	(2.20)*
VolSP(−2)							0.071	(0.84)
VolSP(−3)							0.026	(0.18)
VolRet(−1)							−0.001	(−0.31)
VolRet(−2)							−0.0003	(−0.11)
VolRet(−3)							0.01	(2.73)*
Volume(−1)							−0.2E-4	(−0.30)
Volume(−2)							−0.001	(−1.29)
Volume(−3)							−0.5E-4	(−0.03)

(continued)

TABLE 1 (*Continued*)

					Crises 1			
$x^2(9)$ *p*-value	0.99		0.53		0.46		0.07	
QPS	0.038		0.040		0.036		0.031	0.039
GBS	0.014		0.014		0.009		0.008	0.002
AL	0.903		0.918		0.921		0.927	0.896
Incorrect	8		8		8		6	8
Type I	0.024		0.023		0.020		0.017	1.000
Type II	0.844		0.081		0.799		0.698	0.000
				Crises 2				
Constant	−1.280	(−3.31)						
Spread2(−1)	0.110	(1.79)						
Spread2(−2)	−0.080	(−1.07)						
Spread2(−3)	0.020	(0.39)						
Excash(−1)	−0.040	(2.40)*						
Excash(−2)	0.002	(0.13)						
Excash(−3)	−0.009	(−0.63)						
ClearNY(−1)	−0.7E-5	(−0.91)						
ClearNY(−2)	0.2E-5	(0.28)						
ClearNY(−3)	−0.1E-4	(−2.00)*						
Constant			4.261	(0.23)				
Return(−1)			−0.009	(2.31)*				
Return(−2)			−0.002	(−0.56)				
Return(−3)			0.009	(2.51)*				
Loans(−1)			0.001	(0.21)				
Loans(−2)			−0.002	(−0.73)				
Loans(−3)			0.005	(0.81)				
Spread1(−1)			−0.566	(−1.85)				
Spread1(−2)			0.605	(1.28)				
Spread1(−3)			−0.435	(−1.39)				
Constant					−1.900	(−13.68)		
Money(−1)					0.003	(0.92)		
Money(−2)					0.0008	(0.21)		
Money(−3)					−0.001	(−0.37)		
DC(−1)					−16.15	(−1.58)		
DC(−2)					−18.18	(−1.73)		
DC(−3)					−9.51	(−1.02)		

(*continued*)

TABLE 1 (*Continued*)

			Crises 2			
Constant				−1.493	(−4.44)	
VolSP(−1)				0.037	(0.67)	
VolSP(−2)				0.115	(1.75)	
VolSP(−3)				0.011	(0.21)	
VolRet(−1)				−0.002	(−0.42)	
VolRet(−2)				−0.0003	(−0.08)	
VolRet(−3)				0.018	(2.87)*	
Volume(−1)				−0.6E-4	(−0.92)	
Volume(−2)				−0.0001	(−1.75)	
Volume(−3)				−0.4E-4	(−0.64)	
$x^2(9)$ p-value	0.12	0.06	0.63	0.15		
QPS	0.048	0.059	0.068	0.064		0.073
GBS	0.023	0.005	0.017	0.018		0.001
AL	0.884	0.900	0.864	0.871		0.858
Incorrect	12	12	15	15		15
Type I	0.039	0.035	0.045	0.043		1.000
Type II	0.458	0.593	0.675	0.658		0.000

NOTES: QPS is the Brier quadratic probability score, GBS is the global calibration score, AL is the (geometric) average likelihood, Incorrect cases gives the number of times the model predicts the event that actually occurred with less than .5 probability, type I is the average probability of a false alarm, type II is the average probability of missing the signal. t-statistics are in parentheses. Spread1 is the difference between the rate on long term railroad bonds and the commercial paper rate. Spread2 is the difference between the U.S. call rate and the U.K. call rate. Return is the monthly return on a value-weighted railroad stock index (adjusted to take into account cash dividend payments) computed using Cowles data. VolRet and VolSP measurethe volatility of returns and of the spread between the call and the bond rate, Volume is the trading volume at NYSE, Excash refers to the excess cash reserves of New York banks (relative to the 25% level), ClearNY to the unexpected number of clearings in New York, Loans to the level of excess loans of New York banks relative to their trend, Money to unexpected movements in the money supply and DC to unexpected movements in the deposit to currency ratio. Crisis 1 is a dummy series with a 1 when a crisis starts (is in progress). Crisis 2 is a dummy series with a 1 when a crisis is in progress.

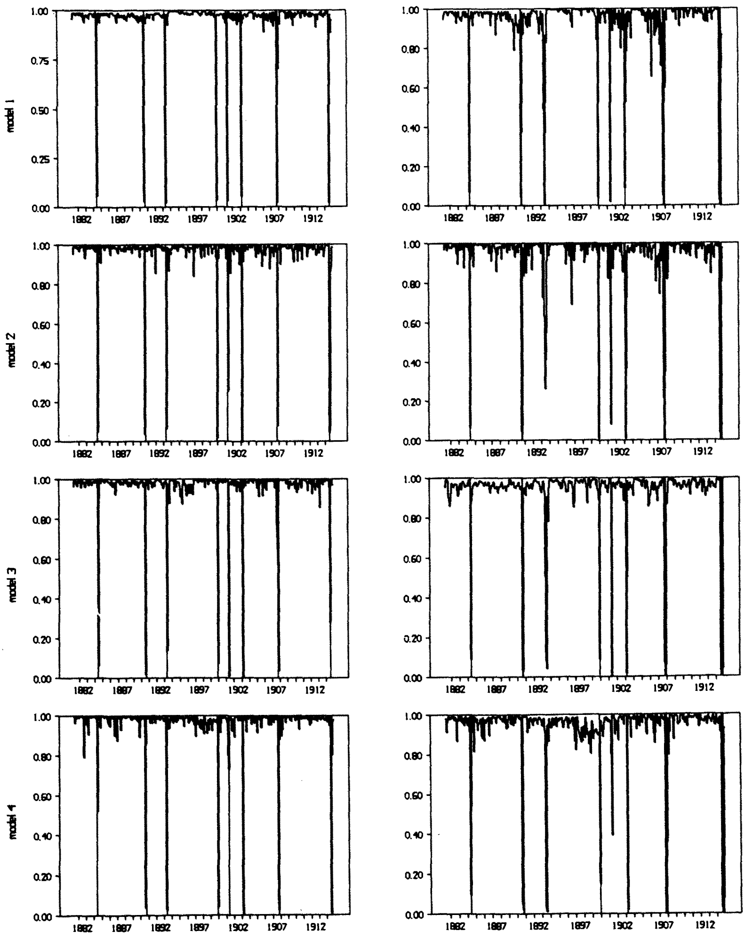

FIG. 1. Recursive Probability Plots

walk in standard forecasting exercises is used as a benchmark to gauge the performance of more structural models. Figure 1 contains recursive probability plots for models 1 through 4. The panels on the left refer to the first crisis series, the panels on the right to the second crisis series. Crisis dates are marked by vertical bars.

The results contained in Table I and in Figure 1 indicate that the agricultural-seasonal hypothesis, the credit-business cycle hypothesis and the monetary hypothesis are all unsuccessful in predicting crises. Abnormally high stock returns three months ahead and unexpected movements in the money supply or in cash reserves two months ahead have some explanatory power for the probability of crisis but they do not predict future events with sufficient precision. The overall fit of these three models, as measured by QPS, GBS, and AL, is reasonable. Model 3 is slightly superior when the first crisis series is used while the performance is more mixed when the second crisis series is used. This reasonable forecasting performance is, however, entirely concentrated at noncrisis dates. While the probability of a false alarm is very small (2–3 percent), all three models fail to predict every crisis in the sample with at least 50 percent probability, and the average probability of missing the signal is around 80 percent.

The bubble theory seems to be more successful in explaining and predicting the occurrence of crises. Abnormally high volatility in stock returns and high volatility in the domestic interest rate spread lead crises by three months and one month, respectively, and the model predicts the occurrence of the 1884 and the 1901 crises with at least 50 percent probability. Both crises were associated with exceptional stock market disturbances due to sales of U.S. securities by British financial institutions (see Sprague, pp. 108–13 and Friedman and Schwartz, pp. 100–101) and to the collapse of Northern Pacific stock (see Friedman and Schwartz, p. 149). In all other episodes, however, the predictive ability of the model is very low.

The visual superiority of model 4 which emerges from Figure 1 is also supported by a formal examination of its predictive ability. Model 4 is better according to all but one forecasting diagnostic. It has the lowest QPS, the highest AL, the lowest number of incorrect cases, and the second lowest GBS statistic. In addition, the average probability of missing the signal drops below 70 percent.

Since the first two theories predict that crises are more likely to occur at particular points of the seasonal and of the business cycle, it is worthwhile to examine whether the predictive content of the first two models improves when specific seasonal and cyclical indicators are used. Table 2 presents the results obtained when the regressors are (i) either seasonal dummies or (ii) the seasonal components of excess cash reserves (Excash Seas), of the deposit to currency ratio (DC Seas), of the number of clearings in New York (ClearNY Seas), and of the international spread between short-term rates (Spread1 Seas) or (iii) the cyclical components of pig iron production (Pigiron Cyc) and of the spread between the bond and the commercial rates (Spread2 Cyc). The seasonal component of each series is constructed by taking the predicted value of a regression of the series on twelve dummies. Cyclical components are computed as the residuals of a regression of the detrended level of the variables on twelve seasonal dummies.[5]

I find that the probability of crises is seasonal. For both crisis series several dummies are significant and the ones for May and August have the highest explanatory power. However, the predictive ability of a seasonal dummy model is low (except perhaps for the 1884 crisis). A similar result holds when the seasonal component of the excess cash reserves in New York banks, of the deposit-to-currency ratio, of the number of clearings in New York, and of the international interest rate spreads are used as independent variables in the regression. When I examine the explanatory power of cyclical indicators Table 2 reveals that only the cyclical component of the

5. I also constructed the seasonal and the cyclical components of the series using frequency domain masking of the Fourier transform of the series. Also, in place of pig iron production, I have examined the performance of a model where the industrial production series recently constructed by Miron and Romer (1990) is used. The results produced were very similar and therefore omitted.

TABLE 2

RECURSIVE PROBIT ESTIMATION: SEASONAL DUMMIES, SEASONAL AND CYCLICAL COMPONENTS
SAMPLE 1880,1–1914,12

	Crises 1			Crises 2		
December	−7.94 (−0.52)			−7.89 (−0.46)		
January	−1.90 (−4.40)*			−1.57 (−4.60)*		
February	−7.94 (−0.52)			−1.57 (−4.60)		
March	−1.90 (−4.40)*			−1.57 (−4.60)*		
April	−7.94 (−0.52)			−1.57 (−4.60)*		
May	−1.57 (−4.60)*			−1.57 (−4.60)*		
June	−7.94 (−0.52)			−1.90 (−4.40)*		
July	−1.90 (−4.40)*			−1.57 (−4.60)*		
August	−1.57 (−4.60)*			−1.90 (−4.40)*		
September	−7.94 (−0.52)			−7.89 (−0.46)		
October	−1.90 (−4.40)*			−1.90 (−4.40)*		
November	−7.94 (−0.52)			−7.89 (−0.46)		
Constant		−188.54 (−1.88)			−29.05 (−0.63)	
Spread1 Seas (−2)		−4.47 (−1.27)			−0.009 (−0.005)	
Excash Seas (−2)		−0.10 (−1.15)			−0.026 (−0.39)	
Excash Seas (−3)		−0.32 (−2.06)*			−0.022 (−0.24)	
ClearNY Seas (−2)		0.0001 (2.05)*			0.00003 (1.04)	
ClearNY Seas (−3)		−0.00003 (−0.65)			−0.00007 (−1.81)	
DC Seas (−1)		503.87 (1.86)			96.42 (0.77)	
Constant			−2.15 (−12.82)			−2.00 (−13.52)
Pigiron Cyc (−1)			0.07 (0.08)			−0.04 (−0.80)
Pigiron Cyc (−2)			−0.14 (−1.31)			0.05 (0.53)
Pigiron Cyc (−3)			0.07 (1.18)			−0.03 (−0.55)
Spread2 Cyc (−1)			0.08 (1.75)			0.18 (4.28)*
Spread2 Cyc (−2)			0.03 (0.42)			0.02 (0.46)
Spread3 Cyc (−3)			−0.01 (−0.16)			0.005 (0.09)
$x^2(12)$ *p*-value	0.0002			0.000		
x^2 (6) *p*-value		0.221	0.469		0.741	0.000
QPS	0.035	0.078	0.038	0.053	0.097	0.058
GBS	0.005	0.043	0.088	0.008	0.023	0.016
ALd	0.931	0.919	0.913	0.899	0.863	0.881
Incorrect Cases	8	8	8	12	15	14
Type I	0.018	0.039	0.021	0.034	0.049	0.039
Type II	0.791	0.850	0.844	0.523	0.715	0.549

NOTES: QPS is the Brier quadratic probability score, GBS is the global calibration score, AL is the (geometric) average likelihood, Incorrect cases gives the number of times the model predicts the event that actually occurred with less than .5 probability, type I is the average probabilityo f a false alarm, type II is the average probability of missing the signal. *t*-statistics are in parentheses. Spread1 Seas is the seasonal component of the difference between the rate on long-term railroad bonds and the commercial paper rate. Excash Seas refers to the seasonal component of excess cash reserves of New York banks (relative to the 25% level), ClearNY Seas to the seasonal component of the unexpected number of clearings in New York, DC Seas to the seasonal component of the deposit to currency ratio. Spread2 Cyc is the cyclical component of the difference between the U.S. call rate and the U.K. call rate and Pigiron Cyc is the cyclical component of pigiron production. Crisis 1 is a dummy series with a 1 when a crisis starts. Crisis 2 is a dummy series with a 1 when a crisis is in progress.

spread lagged three months is significant for the second crisis series. None of the cyclical components is significant for the first crisis series and the forecasting ability of this model is very unsatisfactory.

To further examine the merits of the seasonal hypothesis I also checked whether the level of either the D/C ratio or the excess cash reserves of New York banks or their unexpected movements (constructed as the recursive residuals of univariate AR(13) regressions) in a particular month of the year are important in explaining movements in the probability of crises. I find that there is a monthly specific effect in the D/C ratio but that the forecasting ability of all models used is poor.

From the results obtained so far several conclusions can be drawn. First, there are variables that are significant in revealing economic conditions conducive to crises. Second, while the seasonal cycle may have some role in explaining the probability of crises, all the cyclical indicators I used provide no information on the probability of a crisis. Third, the earliest signs for the presence of those disturbances that may lead to crises appear in the level of stock market returns and their volatility. Fourth, since measures of recursive volatility of the spread of domestic interest rates show abnormal behavior in at least two crises, the results contradict the finding of Gorton (1989) that crises were systematic, in the sense that a set of statistical relationships need not hold at every date in the sample. Fifth, since in none of the regressions performed does the D/C ratio, its unexpected movements, or its seasonal component act as a leading indicator for crises, it is unlikely that crises were induced by runs on banks. Rather, bank runs seemed to be the endogenous outcome of a fall in public confidence following the outburst of a crisis. Finally, the evidence also suggests that crises were not all statistically alike and that their generation mechanisms differed. While some crises were predictable, in other occasions no variable was capable of explaining or predicting the degeneration of stringencies into financial crises. This last result, however, may obtain simply because there are only few crisis dates in a sample with 408 observations (8 or 15 depending on what crises series is used). That is, models may be unable to predict outliers simply because outliers with similar features are too infrequent in the sample.

To overcome this problem I employ an alternative forecasting technique, originally developed in duration analysis (see Lancaster 1979) and recently popularized in macroeconomics by Diebold and Rudebush (1990). The basic element of the technique is the hazard function of the data which measures the conditional probability that a crisis occurs at t, given that it has not exploded earlier and that the last crisis ended t-s periods ago. Therefore, the hazard function provides a convenient tool to determine whether crises could have been predicted using the information contained in the historical spans of time elapsed between crises.

The derivative of the hazard function with respect to time provides a formal measure of the duration dependence of the phenomena. If the hazard function displays positive duration dependence, the probability that a crisis will explode increases with the length of time elapsed from the last crisis. If the hazard function displays no duration dependence (that is, if the derivative of the hazard function with respect to time is constant), the spells of time between crises have no pattern, and the information contained in the spells cannot be used to forecast when the next crisis will occur. By conditioning on the minimum duration of a spell, we can also reexamine the seasonal and the cyclical theory of crises from an alternative point of view. If positive duration dependence emerges once we condition on a minimum duration of twelve or, say, twenty-four to sixty months, this constitutes evidence that crises may have been seasonal or cyclical in nature. To test if the hazard function displays any duration dependence, I employ a nonparametric technique developed by Shapiro and Wilk (1972) and modified by Stephens (1983) to account for the minimum duration of the spells. The technique is powerful since an exact small sample distribution exists even for samples with only three observations. Therefore inference is not conditional on unwarranted asymptotic statements.

Table 3 reports the p-values of the test[6] when the hazard function is constructed recursively. That is, for each $q = 4, \ldots 8$, the test assesses if the information contained in the previous q-1 spells helps to predict when the next crisis will occur. In all but one case and for both crisis series, the null hypothesis of no-duration-dependence is not rejected. Only when we condition on the information that there must be a twenty-eight-month or longer minimum delay between crises, is the hypothesis of no-duration-dependence rejected. Particularly significant and consistent with previous results is the nonrejection of the null hypothesis of no-duration-dependence when the minimum duration is assumed to be twelve months. Therefore, even though the probability of crises may be seasonal, this information is not useful to forecast any of the last five crises in the sample.

Finally, I address the question of whether agents, endowed with the econometric techniques used in the paper, could have avoided wealth losses associated with crises. Consider for this purpose the following simple 50 percent cut-off rule to guide portfolio investments: if the probability of a crisis is less than 50 percent, invest 100 percent of wealth in risky assets. If the probability of a crisis is greater than 50 percent, invest 100 percent of wealth in riskless assets. With this portfolio strategy, agents would have been able to cut their losses only in the 1884 and 1901 crises using model 4. To quantify the gains obtained from this strategy it is necessary to have a measure of the riskless rate. Given the structure of financial markets of the period such a rate does not appear to exist. The time rate is the closest substitute of a riskless rate and it is used here as a benchmark riskless asset. Over the 1880–1914 period, the average expost excess return of a strategy that switches from a stock market index to time deposits when a crisis is predicted with at least 50 percent probability relative to a buy-and-hold strategy in a stock market index would have been 0.03 percent.[7] This excess return is minuscule when compared, for example,

6. The values of the table are linearly interpolated from the tables of Shapiro and Wilk. Since there is evidence that seasonal indicators may help to explain the probability of crisis, it may be possible that the hazard function shifts with the season making the analysis invalid. I am unable to verify this hypothesis, since, once I condition on the season, there are less than three observations per cell and the Shapiro and Wilk test cannot be applied. However, in a regression of the durations on seasonal dummies, none of the coefficients on the dummies was significant.

7. The magnitude of the gains is robust and independent of which of the three available rates (time, commercial, or bond rate) is used in the calculation.

TABLE 3

NONPARAMETRIC TESTS FOR DURATION DEPENDENCE OF CRISES; SAMPLE 1880,1–1914,12

	Crises 1		Crises 2	
	value	p-value	value	p-value
$q = 4$				
Shapiro and Wilk W	0.4352	0.5661	0.4417	0.5434
Stephens $WW(\gamma = 2)$	0.4540	0.3324	0.4149	0.2692
Stephens $WW(\gamma = 4)$	0.3930	0.2495	0.3557	0.1974
Stephens $WW(\gamma = 6)$	0.3272	0.1546	0.2931	0.1029
$q = 5$				
Shapiro and Wilk W	0.2557	0.4180	0.2764	0.4753
Stephens $WW(\gamma = 2)$	0.2761	0.3045	0.2687	0.2943
Stephens $WW(\gamma = 4)$	0.2427	0.2139	0.2359	0.2226
Stephens $WW(\gamma = 6)$	0.2094	0.1484	0.2033	0.1346
Stephens $WW(\gamma = 8)$	0.1767	0.0777	0.1713	0.0622
$q = 6$				
Shapiro and Wilk W	0.2025	0.4111	0.2204	0.4933
Stephens $WW(\gamma = 2)$	0.2066	0.2828	0.2091	0.2984
Stephens $WW(\gamma = 4)$	0.1867	0.2031	0.1887	0.2247
Stephens $WW(\gamma = 6)$	0.1670	0.1567	0.1687	0.1651
Stephens $WW(\gamma = 10)$	0.1293	0.075	0.1302	0.0810
$q = 7$				
Shapiro and Wilk W	0.2017	0.5331	0.2228	0.5872
Stephens $WW(\gamma = 2)$	0.1965	0.3923	0.2045	0.4095
Stephens $WW(\gamma = 4)$	0.1807	0.3315	0.1878	0.3437
Stephens $WW(\gamma = 6)$	0.1652	0.2901	0.1713	0.3172
Stephens $WW(\gamma = 12)$	0.1206	0.1114	0.1239	0.1284
Stephens $WW(\gamma = 28)$	0.0372	0.0000	0.0358	0.0001
$q = 8$				
Shapiro and Wilk W	0.2001	0.5065	0.2076	0.5258
Stephens $WW(\gamma = 2)$	0.1812	0.3642	0.1998	0.3945
Stephens $WW(\gamma = 4)$	0.1799	0.3298	0.1812	0.3402
Stephens $WW(\gamma = 6)$	0.1489	0.2880	0.1656	0.3005
Stephens $WW(\gamma = 12)$	0.1112	0.1321	0.1078	0.1114
Stephens $WW(\gamma = 28)$	0.0265	0.0020	0.0406	0.0021

NOTE: The Shapiro and Wilk W statistic is computed for each q as $W = \frac{(\bar{x} - x_1)^2}{(q - 1)\bar{\sigma}^2}$ where $\bar{x} = \frac{\Sigma_{i=1}^{q} x_i}{q}$, $\bar{\sigma}^2 = \frac{\Sigma_{i=1}^{q} (x_i - \bar{x})^2}{q - 1}$ and where x_i are the ordered durations between crises. The Stephens WW statistic is computed as: $WW(\gamma = s_0) = \frac{(\Sigma_{i=1}^{q} (x_i - \gamma))^2}{q[(q + 1) \Sigma_{i=1}^{q} (x_i - \gamma)^2 - (\Sigma_{i=1}^{q} (x_i - \gamma))^2]}$ where s_0 is the minimum duration, x_i are the ordered statistics and q is an index numbering the durations ($q - 1$ is the number of spells used to predict when the qth crisis will occur). Crisis 1 is a dummy series with a 1 when a crisis is in progress. Crisis 2 is a dummy series with a 1 when a crisis is in progress.

with the average costs of bank failures during crises as reported, for example, by Calomiris and Gorton (1991). Although more conservative cut-off probabilities (for example, switch when a probability of a crisis is 10 percent) would certainly yield more favorable results as the loss function becomes more asymmetric, it is clear that the unpredictable nature of financial crises casts doubts on the ability of simple investment strategies to shield agents living in the National Banking Era from wealth losses associated with crises.

5. CONCLUSIONS

This paper empirically investigates the nature of financial crises in the United States for the period 1880–1914. It is shown that there were variables known to agents one month before the explosion of a crisis that were significant in explaining the economic conditions conducive to crises, that the probability of crises was seasonal, and that business cycle events had little effect on the probability of crises. Despite these "in-sample" findings, the out-of-sample forecasting ability of every model examined was poor. The only exception was a model including measures of volatility of financial aggregates as independent variables that predicted that in 1884 and 1901 the crises with at least 50 percent probability.

Several conclusions can be drawn from this study. First, movements in financial variables typically associated with money market stringency and financial market weakness (an increase in short-term interest rates, a drop in asset prices, a sharp reduction in banks' excess cash reserves) appear to be relevant to predict some of the crises in the sample. On at least two occasions agents could have avoided some of the wealth losses using available information and simple forecasting rules. In the six other occasions, however, the signals given by financial and monetary markets were not sufficient to accurately predict the outburst of a crisis. To explain these episodes one therefore has to rely on the occurrence of an extraordinary event not captured by the forecasting model or on the presence of self-fulfilling expectations. Second, while measures of financial market volatility are useful in predicting two crises, in no occasion do variations in the deposit-to-currency ratio act as a leading indicator for crises. Therefore, it unlikely that bank runs "caused" financial crises. Instead, bank runs were probably the endogenous outcome of severe disturbances in financial markets. Third, given the various degree of predictability of different crises, it is unlikely that the mechanism generating the eight crises in the sample was the same.

Two caveats need to be mentioned before embracing these conclusions. One concerns the nature of the data. The monthly average series that are available are not entirely appropriate because they tend to smooth out those outliers that could be useful in predicting the occurrence of crises. Ideally, in conducting these exercises one would like to have point-in-time data for all the series.

The second concern involves the sampling interval used. A month may be too long an interval of time to predict the occurrence of certain crises. Since the earlier crises included in the sample lasted less than a month, the sampling of the variables of interest may be too infrequent to produce an adequate forecasting model. A study using weekly data is therefore necessary to cross-validate the conclusions obtained in this paper.

LITERATURE CITED

Andrew, Piatt A., "The Influence of Crops upon Business in America." *Quarterly Journal of Economics* 20 (1907), 323–51.

———. *Statistics for U.S., 1867–1909*. 61st Congress, 2nd Session, Senate Document 570, vol. 6, n. 5606, Washington, D.C.: National Monetary Commission, 1910.

Barro, Robert. "Interest Rate Targeting." *Journal of Monetary Economics* 23 (1989), 1–35.

Bordo, Mike. "The Impact and the International Transmission of Financial Crises: Some Historical Evidence." *Rivista di Storia Economica* 2 (1985), 41–78.

Cagan, Phil. *The Determinants and the Effects of Changes in the Stock of Money.* New York: Columbia University Press, 1965.

Calomiris, Charles, and Gary Gorton. "The Origin of Banking Panics: Models, Facts and Bank Regulation." In *Financial Markets and Financial Crises,* Glen Hubbard, editor, pp. 110–57. Chicago, Il.: Chicago University Press for the NBER, 1991.

Canova, Fabio. "The Sources of Financial Crises: Pre and Post Fed Evidence." *International Economic Review* 32 (1991), 689–713.

Chari, V. V. "Banking without Deposit Insurance or Bank Panics: Lessons from a Model of the U.S. National Banking System." Federal Reserve Bank of Minneapolis *Quarterly Review* (Summer 1989), 3–19.

Chari, V. V., and Ravi Jagannatthan. "Banking Panics, Information, and Rational Expectations Equilibrium." *Journal of Finance* 43 (1988), 749–60.

Clark, Truman. "Interest Rates Seasonals and the Federal Reserve." *Journal of Political Economy* 94(2) (1986), 76–123.

Comptroller of the Currency. *Reports.* Washington, D.C.: Government Printing Office, 1880–1915.

Cowles, Alfred III, and Associates. *Common Stock Indexes,* 2d ed. Cowles Commission Monograph no. 3, Bloomington, Ind.: Principia Press, Inc., 1939.

Dewald, William. "The National Monetary Commission: A Look Back." *Journal of Money, Credit, and Banking* 4 (November 1972), 930–56.

Diamond, Peter, and Phil Dybvig. "Bank Run, Deposit Insurance and Liquidity." *Journal of Political Economy* 91 (1983), 401–19.

Diebold, Frank, and Glen Rudebush. "Scoring the Leading Indicators." *Journal of Business* 62 (1989), 212–33.

______. "A Nonparametric Investigation of the Duration Dependence of the American Business Cycle." *Journal of Political Economy* 99 (1990), 596–616.

Eichengreen, Barry, and Richard Portes. "The Anatomy of Financial Crises." In *Treats to International Financial Stability,* edited by R. Portes and A. Swoboda, pp. 10–58. New York: Cambridge University Press, 1987.

Fisher, Erwin. "The Debt Deflation Theory of the Great Depression." *Econometrica* 1 (1933), 537–57.

Friedman, Milton, and Anna Schwartz. *A Monetary History of the United States, 1867–1960.* Princeton University Press, 1963.

Gorton, Gary. "Banking Panics and Business Cycles." *Oxford Economic Papers* 60 (1989), 751–81.

Goodhart, Charles A. E. *The Business of Banking 1891–1914.* London: Weindenfield & Nicholson, 1972.

Jacklin, Charles J. "Demand Deposit, Trading Restrictions and Risk Sharing." In *Contractual Arrangements for Intertemporal Trade,* edited by Edward Prescott and Neil Wallace. Minneapolis: University of Minnesota Press, 1987.

Jevons, Stanley. *Investigation in Currency and Finance.* London: Macmillan, 1884.

Juglar, Clemens, and De Courcy W. Thom. *A Brief History of Panics.* New York: M. Kelley Publisher, 1915.

Kemmerer, E. W. *Seasonal Variation in the Demand for Currency and Capital.* Washington, D.C.: National Monetary Commission, 22, 1910.

Kindleberger, Charles P. *Manias, Panics and Crashes: A History of Financial Crises.* New York: Basic Books, 1978.

Lancaster, Tony. "Econometric Methods for the Duration of Unemployment." *Econometrica* 47 (1979), 939–56.

Lauck, Jett. *The Causes of the Panic of 1893.* Boston: Houghton, Mifflin and Co., 1907.

Macaulay, Fredrick. *Some Theoretical Problems Suggested by Movements in Interest Rates, Bonds Yields and Stock Prices in the U.S. since 1856.* New York: National Bureau of Economic Research, 1938.

Meltzer, Allan. "Rational Expectations, Risk, Uncertainty and Market Responses." In *Crises in the Economic and Financial Structure,* edited by Paul Watchel, pp. 3–22. Lexington, Mass.: Lexington Books, 1982.

Minsky, Hyman. "A Theory of Systematic Fragility." In *Financial Crises: Institutions and Markets in a Fragile Environment,* edited by E. J. Altman and A. W. Sametz. New York: Wiley International, 1977.

Miron, Jeffrey A. "Financial Panics, the Seasonality of Nominal Interest Rates, and the Founding of the Fed." *American Economic Review* 76 (1986), 125–40.

Miron, Jeffrey A., and Christina Romer. "A New Monthly Index of Industrial Production." *The Journal of Economic History* 50 (1990), 321–38.

Mitchell, Wesley. *Business Cycles.* Berkeley, Calif.: University of California Press, 1913.

Morgenstern, Oskar. *International Financial Transmission and Business Cycles.* Princeton, N.J.: Princeton University Press, 1959.

National Monetary Commission. *Reports.* Washington, D.C.: Senate Documents 5606-5642, 1910.

New York Press. *A Brief Popular Account of All Financial Panics and Revulsions in the United States from 1690 to 1857.* New York: J. C. Haney Publisher, 1857.

Palgrave Inglis, R. H. *Statistics for the U.K., France and Germany 1867–1908.* 61st Congress, 2nd Session, Senate Document 578, vol. 31, n. 5630, Washington, D.C.: National Monetary Commission, 1910.

Schwert, William. "Business Cycles, Financial Crises, and Stock Volatility." *Carnegie-Rochester Conference Series on Public Policy* 31 (1989), 83–126.

Shapiro, S., and M. Wilk. "An Analysis of Variance Test for Exponential Distribution (Complete Samples)." *Technometrics* 14 (1972), 355–70.

Sprague, O. M. W. "The American Crises of 1907." *Economic Journal* 28 (1908), 353–403.

______. *History of Crises under the National Banking System.* 61st Congress, 2nd Session, Senate Document 538, Washington, D.C.: National Monetary Commission, 1910.

______. "The Crises of 1914 in the U.S." *American Economic Review* 5 (1915), 499–533.

Stephens, M. "On the W Test for Exponentiality with Origin Known." *Technometrics* 20 (1983), 33–35.

Waldo, Douglas. "Bank Runs, the Deposit to Currency Ratio and the Interest Rate." *Journal of Monetary Economics* 15 (1985), 269–78.

Williamson, Steven. "Bank Failures, Financial Restrictions, and Aggregate Fluctuations: Canada and United States." Federal Reserve Bank of Minneapolis *Quarterly Review* (Summer 1989), 20–40.

Wilson, Jack, Richard Sylla, and Charles Jones. "Financial Market Volatility, Panics under The National Banking System before 1914, and Volatility in the Long Run 1830–1988." In *Crises and Panics and Historical Perspective,* edited by Eugene White. Dow Jones/Irwin: Homewood, 1990.

Working, H. "A Note on the Correlation of First Differences of Averages in Random Chains." *Econometrics* 28 (1960), 916–18.