Contagion Risk in Banking

Dirk Schoenmaker*
Ministry of Finance, the Netherlands

Abstract

A controversial issue in the literature on banking regulation is whether there is contagion risk, or not. This paper derives a framework to test for contagion risk and applies it to a data set of monthly bank failures under the US National Banking System from 1880 till 1936. To capture the count nature of bank failure data, an autoregressive Poisson model is used. The empirical results indicate that there is contagion risk in banking. An initial failure could generate further failures without intervention by the authorities. This finding suggests that there may be a role for the central bank as lender of last resort to assist ailing banks, whose failure is expected to have a systemic impact.

> *In wild periods of alarm, one failure makes many, and the best way to prevent the derivative failures is to arrest the primary failure which causes them.*
>
> Bagehot, *Lombard Street* (1873, p.51-2)

1 Introduction

The debate on the need for banking regulation and supervision depends critically on the question whether there is contagion risk in banking, or not. Contagion risk—which is also referred to as systemic risk—is here defined as the risk that financial difficulties at one or more bank(s) spill over to a large number of other banks or the financial system as a whole. There has been little attempt so far to measure contagion risk. Reviewing the limited empirical evidence of bank contagion, Kaufman (1994) comes to the conclusion that concerns about systemic stability have been greatly exaggerated.

The paper highlights some shortcomings of previous studies on contagion risk.

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First, some of these studies (e.g. Grossman, 1993) use ordinary least squares regressions to analyse bank failures. But a least squares regression may lead to mis-specifications, since bank failure time series consist of count data—that are non-negative integers—recording the number of events occurring in a given interval. To deal explicitly with the count nature of bank failure data, we use an autoregressive Poisson regression model developed by Shephard (1995).

More importantly, some of these mainly US studies (e.g. Aharony and Swary, 1983; Swary, 1986) examine possible contagion effects during periods in which the central bank played an active role as lender of last resort to prevent contagious bank failures. Consequently, the lack of evidence of contagion from such periods does not disprove the possibility of bank contagion. To avoid this pitfall, we examine data on bank failures under the US National Banking System, founded in 1864, some fifty years before the establishment of the Federal Reserve System.

Interestingly, the results from our empirical study are consistent with the existence of contagion risk and are thus opposite to those of Kaufman (1994). An initial failure could generate further failures without intervention by the authorities. This seems to support the view that lender of last resort assistance from the central bank to individual banks may be justified *in some cases* to prevent the potential spillover effects of bank failures (e.g. Solow, 1982; Goodhart, 1987; Summers, 1991). If there is an important role for public intervention in the form of emergency assistance in times of crisis, then it is arguable that the banking sector, as recipient of this liquidity support, should be regulated and supervised (i.e. monitored) to contain the adverse selection and moral hazard effects of such intervention (e.g. Folkerts-Landau and Garber, 1992; Goodhart and Schoenmaker, 1995).

The paper proceeds as follows. In Section 2, we review the theoretical framework for bank contagion. Although the literature on bank runs (e.g. Diamond and Dybvig, 1983; Chari and Jagannathan, 1988) provides explanations for runs on individual banks, it does not explain why depositors at many banks withdraw their deposits simultaneously, generating a banking panic. The possible channels for the spread of contagion are explored. Next, we discuss some of the earlier empirical studies on contagion risk. In Section 3, we develop a methodology to test for contagion risk. The idea is that we can speak of contagion risk when bank failures are found to be dependent (i.e. correlated) after controlling for common factors, such as macro-economic variables. The model is tested with bank failure data from the pre-Federal Reserve period. As indicated above, the results are consistent with the existence of bank contagion. The conclusions follow in Section 4.

2 Contagion risk in banking

The phenomenon of bank runs has been rigorously modelled in the literature.[1] A

[1] See Bhattacharya and Thakor (1993) for a recent and comprehensive survey of banking theory.

first set of models (e.g. Diamond and Dybvig, 1983; Postlewaite and Vives, 1987) assumes consumption risk—reflected in a stochastic withdrawal of deposits—and riskless, but illiquid, investments. The illiquidity of these investments provides the rationale for the existence of banks and for their vulnerability to runs. Excessive withdrawals of deposits would force a bank into costly liquidation. Hence, if a depositor expects that others will withdraw, he will also withdraw to avoid losses from such a liquidation. The Diamond-Dybvig model gives rise to multiple equilibria, including a bank run equilibrium. A bank run is caused by a shift in expectations, which can depend on some commonly observed factor such as a sunspot (it need not be anything fundamental about the bank's condition).

In a more realistic setting, a second set of bank run models (e.g. Chari and Jagannathan, 1988; Gorton, 1985) introduces investment risk in addition to consumption risk. Asymmetric information between the bank and its depositors on the true value of loans is a key element of these models. In the Chari-Jagannathan model, only a fraction of depositors receives information on the prospects of loans. Uninformed depositors, however, do not know whether large deposit withdrawals are caused by an increase in the fraction of early consumers and/or by information on a low outcome of loans. Given that a long withdrawal queue could be caused by bad information about a bank's solvency, the rational response of the uninformed depositor is to join the queue as well and withdraw early. An information-induced bank run can thus occur, even if no one receives a bad signal. The Chari-Jagannathan and Diamond-Dybvig models differ in that bank runs in the former start with fears of insolvency of particular banks, while bank runs in the latter are based on self-fulfilling beliefs.

Although the bank run literature provides explanations for runs on individual banks, it does not explain why depositors at many banks withdraw their deposits simultaneously, generating a banking panic (Calomiris and Gorton, 1991). The contagion effects of bank runs need to be treated explicitly in a model of banking panic. The risk of contagion in banking—also referred to as systemic risk—is here defined as the risk that financial difficulties at one or more bank(s) spill over to a large number of other banks or the financial system as a whole. Contagion can spread either through the information channel or the credit channel.

Starting with the information channel, Aharony and Swary (1983) make a distinction between pure (industry specific) contagion and noisy (firm specific) contagion. Pure contagion occurs when negative information—such as fraud or losses on specific risky investments—about one bank adversely affects all other banks, including those that have nothing in common with the first bank. Noisy or firm specific contagion arises when the failure of one bank reveals a bad (but noisy) signal regarding other banks with common characteristics. If one bank fails, then other banks with a similar asset and liability structure—and therefore vulnerable to the same economic shocks—may also face a run.[2] In a world with imperfect information, runs on other banks can be triggered by perceived—and thus not necessarily actual—similarities with the failing bank.

Turning to the credit channel, there is a complex web of linkages between banks in the interbank funding market, the over-the-counter (OTC) derivatives market, and the payment system (e.g. Guttentag and Herring, 1987; Schoenmaker, 1995). The size of interbank credit lines is exempt from large exposure rules and is usually related to the size of the borrowing bank and not of the lending bank. Surviving banks can thus have substantial claims on the failing bank and may subsequently fail.[3] Moreover, there is a lack of timely data on interbank exposures. Market participants know that interbank positions may be very large, but the size of particular bilateral positions is not known. In the event of a bank failure, market participants do not know which banks have unsatisfied claims against the failing bank. This in turn may generate a general loss of confidence in the interbank market.

2.1 Earlier studies on contagion risk

Although the theoretical framework to show the possibility of contagion in banking has been well-developed, little effort has been expended to quantify the likelihood and intensity of contagious bank runs. In a recent paper, Kaufman (1994) reviews the empirical evidence of bank contagion. The first question examined is how broad contagion can spread within the banking sector. A number of studies have measured the breadth of spillover from a bank failure by the loss to shareholders of surviving banks as evidenced in share returns (e.g. Aharony and Swary, 1983; Swary, 1986; Peavy and Hempel, 1988). Using stock market data, these studies examine the post announcement share performance. Negative abnormal returns are an indicator for contagion effects. Following the earlier-mentioned distinction between industry specific and firm specific contagion, Kaufman finds only some support for the latter in these empirical studies. An initial failure does not cause further failures directly, but information about the first, or first few, bank(s) in difficulties reveals information about (some) other banks. The problems causing defaults stem thus from a common factor.

In a similar review of the empirical literature, Saunders (1987) finds little evidence of contagion. However, a major drawback of these (mainly US) studies is that most of them examine possible contagion effects during periods in which the Federal Reserve played an active role as lender of last resort to prevent conta-

[2] A recent example of contagion via the information channel is provided by the liquidation of Barings in February 1995. After the Barings collapse, most other UK merchant banks faced funding problems in the wholesale market.

[3] See, for example, the failure of Continental Illinois in 1984. Continental acted as correspondent bank for nearly 1,000 banks at the time. Sixty-six banks had uninsured deposits exceeding 100% of their capital, and another 113 banks had deposits between 50 and 100% of their capital. We will discuss this case in more detail below.

gious bank failures.[4] Consequently, this evidence does not disprove the possibility of bank contagion. In the next section, we discuss some recent studies (e.g. Grossman, 1993; Hasan and Dwyer, 1994) investigating bank contagion in the 19th century, before the Federal Reserve was founded. The empirical findings in these studies indicate the existence of contagion risk, though the contagion effects are not found to be very large.

Another mechanism of contagion examined by Kaufman (1994) is the credit channel. Interconnections between banks—via the fed funds market and correspondent balances—speed up the transmission of losses from affected banks to many other banks. A prime example is the earlier-mentioned failure of Continental Illinois in 1984. Continental had a large correspondent banking network and nearly 1,000 banks had deposits at Continental at the time it failed. Sixty-six of these banks had uninsured deposits exceeding 100 percent of their capital, and another 113 had deposits between 50 and 100 percent of their capital (US Department of the Treasury, 1991).

But uninsured depositor losses are unlikely to be very large with a timely closure, since the value of the bank's total assets is unlikely to drop suddenly anywhere close to zero, as Kaufman correctly argues. The full amount was therefore not to be lost, but uncertainty about the precise size of the losses and about the time needed to recover (part of) Continental's assets could have generated runs on these banks.[5] If the uninsured deposits in Continental had not been protected by the Federal Reserve and the Federal Deposit Insurance Corporation (FDIC), its failure might have caused a chain of bank failures.

Finally, it is not sufficient to show that banks face low probabilities of failure in order to downplay possible contagion effects. Benston *et al*. (1986, p.58), for example, provide evidence that the average annual rate of bank failures was not greatly different from the rate of business failures in the 1875-1929 period (i.e. before the multiple bank failures during the Great Depression). Repeating their calculations in Table 1, we find an even stronger result: the average annual bank failure rate (0.43 percent) was less than half of the average annual business failure rate (1.00 percent) during the 1875-1929 period. This difference is due to the fact that our sample of bank failures covers only national banks, while the sample in Benston *et al*. (1986) covers both national and state-chartered banks.

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[4] Saunders (1987) also notes that these studies must be interpreted in light of the fact that the Federal Reserve has clearly sought to prevent contagious bank runs. Thus the lack of clear evidence of contagion may simply indicate that the Fed has largely succeeded.

[5] Kaufman (1994, p.131) asserts that 'actual losses at the Continental were less than five cents on the dollar, which was also *a reasonable estimate* at the time of the failure' (italics added), but fails to provide evidence to support this claim.

Table 1: Bank and business failures in the USA, 1875-1935

Period	*Mean*	*Standard deviation*	*Coefficient of variation*
*Bank failure rate**			
1875-1935	0.84	1.58	2.97
1875-1929	0.43	0.43	0.43
1930-1935	4.61	3.03	1.99
*Business failure rate**			
1875-1935	1.01	0.24	0.06
1875-1929	1.00	0.23	0.05
1930-1935	1.05	0.38	0.14

Source: *Historical Statistics of the United States Colonial Times to 1970*, US Department of Commerce, Washington DC (1975).

* The annual bank (business) failure rate—reported in percent—is calculated as the number of bank (business) failures divided by the total number of banks (concerns in business).

Although the mean of bank failures may be lower than that of business failures, the variation is significantly higher. Following Benston *et al*. (1986), we have calculated the coefficient of variation in order to adjust for the differences in means between the two series. This statistic is 0.43 for the rate of bank failures and only 0.05 for the rate of business failures from 1875 through 1929. This higher variation might, but does not need to, indicate larger contagious effects in banking than in other business sectors.

Reviewing our discussion of the literature, we conclude that a rigorous test of contagion risk can only be done with data from a period without a central bank acting as lender of last resort. In other words, contagion is allowed to spread freely through the banking system. In the next section, we make an attempt to quantify contagion risk with this constraint in mind.

3 Empirical test of contagion risk

3.1 Methodology

In this section, we develop a measure to test for contagion risk, which is defined as the risk that an initial (bank) failure may spill over to the rest of the (banking) industry and cause further (bank) failures. Bank failure time series consist of count data—that are non-negative integers—recording the number of events occurring in a given interval. Some previous studies on contagion (e.g. Grossman, 1993) use ordinary least squares regressions to analyse bank failures. But given the predominance of zeroes and small values and the discrete nature of bank failure data, a least squares regression may lead to mis-specifications. To deal explicitly with the non-negative and discrete nature of count data, such as bank failures, we use the Poisson regression model.[6]

The standard Poisson process assumes that the number of bank failures λ remains constant and that bank failures are independent. In reality, the probability of bank failure may vary over time, violating the first assumption. A generalisation of the Poisson process is to allow the parameter λ to depend on time (Lancaster, 1990). The probability function of the time-dependent Poisson distribution is as follows:

$$Prob\ (y_t\,;\lambda_t) = \frac{e^{-\lambda_t}\lambda_t^{y_t}}{y_t!} \tag{1}$$

where $y_t = 0,1,2,\ldots$ is the number of bank failures at time t, and $\lambda_t > 0$ is the average number of bank failures per unit of time at time t.

In an international survey of bank failures, Heffernan (1995) finds the following macro-economic indicators to be important explanatory variables for the observed variation in the number of bank failures: GDP growth, inflation, interest rates, and exchange rates. Accordingly, we can model the number of failures to depend on a set of macro-economic variables. Since λ_t must be positive, the standard log-linear link function can be applied:

$$\ln \lambda_t = \beta x_t' \tag{2}$$

where x_t' denotes a vector of macro-economic variables at time t, and β is the corresponding vector of parameters.

Given a set of independent observations, the likelihood and log-likelihood functions are as follows:

$$L = \prod_{t=1}^{T} \frac{e^{-\lambda_t}\lambda_t^{y_t}}{y_t!} \tag{3}$$

$$\ln L = -\sum_{t=1}^{T}\lambda_t + \sum_{t=1}^{T} y_t \ln \lambda_t - \sum_{t=1}^{T} \mathrm{In}(y_t!) \tag{4}$$

The log-likelihood function specified in (4) can be maximised by differentiating with respect to the parameter vector β:

$$\frac{\partial \ln L}{\partial \beta} = \sum_{t=1}^{T} x_t (y_t - \lambda_t) = 0 \tag{5}$$

[6] Another model appropriate for the analysis of discrete dependent variables is the probit model. In a recent study, Hasan and Dwyer (1994) estimate probit equations for bank closings during the Free Banking Period in the USA from 1837 through 1863.

The maximum likelihood estimator $\hat{\beta}$ can be found using the Newton-Raphson algorithm (Hamilton, 1994).

The second assumption of the standard Poisson model is that bank failures are independent. This characterises the absence of contagion risk. Individual bank runs are not causally related, though they may have a common factor (such as the above-mentioned macro-economic indicators). By contrast, the notion of bank contagion means that an initial failure may cause further failures by banks which are exposed to the originally failing bank and thus violate the condition of independence. While the initial failure may follow a stochastic process, the secondary failures are then partly determined by the initial failure. An extreme form of dependency is the domino effect: a failure of any single bank entails a chain reaction, such that eventually all the other banks in the system will also fail (Paroush, 1988). A less stringent form of dependency is the situation in which the probability of bank failure conditional on the number of previous failures increases with the number of previous bank failures.

While the standard Poisson model assumes that the dependent variable y_t is independently distributed, Shephard (1995) provides an extension to autoregressive Poisson models.[7] The procedure proposed by Shephard allows the lagged observations to enter additively on a log-linear scale. But the log specification cannot be used as it leads to singularities at $y_t = 0$. To solve this problem, Shephard (1995) approximates ln y_t with a first-order Taylor series around λ_t:

$$z(y_t) = \ln \lambda_t + \frac{y_t - \lambda_t}{\lambda_t} \tag{6}$$

The link function for the autoregressive Poisson model then becomes:

$$\ln \lambda_t = \beta x_t' + \sum_{j=1}^{p} \gamma_j z(y_{t-j}) \tag{7}$$

where γ is the coefficient for the lagged number of bank failures, and p denotes the number of lags. The second term on the right-hand side of (6) can be rewritten as follows: $c_t = (y_t - \lambda_t)/\lambda_t$, where c_t is a martingale difference sequence. Substituting (7) into (6), we get a non-linear autoregression for bank failures y_t with martingale difference errors:

$$z(y_t) = \beta x_t' + \sum_{j=1}^{p} \gamma_j z(y_{t-j}) + c_t \tag{8}$$

According to (8), the number of bank failures is dependent on various macroeconomic indicators and the number of failures in the previous period(s). Recent examples of banking crises with multiple failures are the savings & loans debacle

[7] See, for example, Ljungqvist (1995) for an application of the autoregressive Poisson model to data on initial public offerings (IPO) in Germany from 1970 through 1994.

in the US (1980s) and the Scandinavian banking crisis (early 1990s). It is an empirical question whether the multiple bank failures are caused by a common macro-economic variable, e.g. rising interest rates in the US and a sharp fall in GDP in Scandinavia, perhaps in conjunction with a structural variable such as deregulation, or by interdependency between banks. But to test whether there is risk of contagion in banking (i.e. bank failures are dependent), we have to examine periods in which there was no rescue of banks whose failure was expected to have a systemic impact. In other words, neither the government nor the central bank (as lender of lender resort) assumed an active role in the management of banking crises during these times.

3.2 Data

In order to test for risk of contagion, we examine the US National Banking System, which was established in 1864, fifty years before the foundation of the Federal Reserve System.[8] The *Annual Reports* of the Comptroller of the Currency, the regulator of the national banks, are a rich source of information and report the exact date of each bank failure.[9] The contagion effect, if any, can probably be observed within weeks or months, but not years, after the initial bank failure(s). While our bank failure data are on a daily basis, macro-economic data are only available on a monthly basis. We therefore use monthly series from January 1865 till December 1940. The dependent variable in our Poisson regression model is the number of bank failures per month (BF), which is a non-negative integer.

The macro-economic variables are the level of real output (GDP), the index of stock prices (SP), the price level (P), and the short-term interest rate (R). The level of real output is proxied by pig iron production, the stock price index is the value weighted index of the New York Stock Exchange, the price level is proxied by Snyder's Index, and the interest rate is the commercial paper rate. The Appendix provides a more detailed description of the data and their sources.

Using an augmented Dickey-Fuller test we cannot reject a unit root in the output (GDP), stock price (SP), and price level (P) series. But a unit root can be rejected in the changes of these variables. Accordingly, the regressions are run with the monthly changes in the logarithm of these variables (the differential is taken on a twelve-month basis to eliminate seasonal influences). We also take monthly changes in interest rates (R), as we expect changes rather than the level of interest rates to determine the possible number of bank failures.

3.3 Empirical results

Based on (8), the following model is used for the regressions:

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[8] In its early years, the Federal Reserve did not play an active role as lender of last resort to stem banking crises. This period (1914-33) is known as the real-bills era (see Chapter 17 of Timberlake, 1993).

[9] The Comptroller's *Annual Reports* from 1865 till 1940 are available in the Bank of England library. We would like to thank the Bank for their assistance.

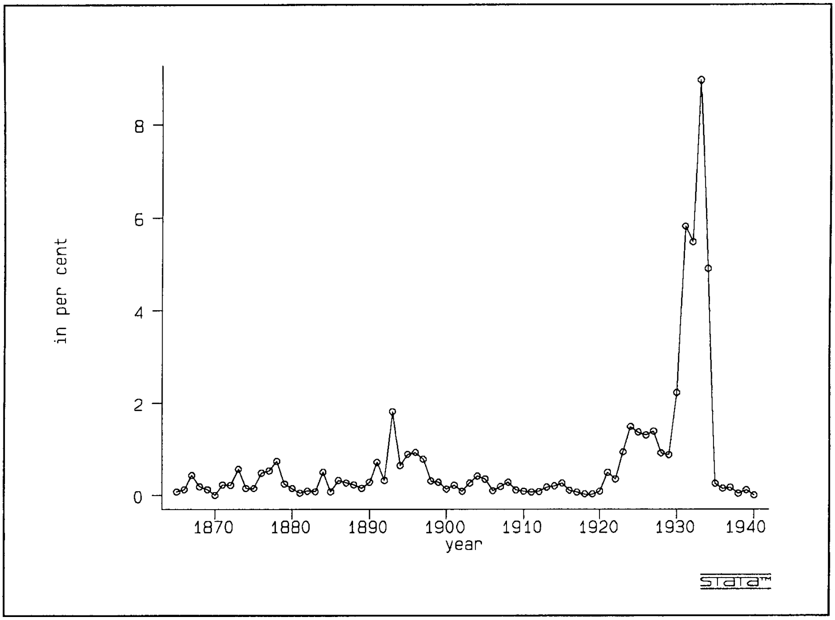
$$z(BF_t) = \alpha + \beta_1 \Delta GDP_t + \beta_2 \Delta SP_t + \beta_3 \Delta P_t + \beta_4 \Delta R_t + \gamma_1 z(BF_{t-1}) + c_t \tag{9}$$

The null hypothesis is that bank failures are independent, which implies $\gamma_1 = 0$. Only when gamma is significantly different from zero while controlling for macro-economic influences, we can reject our null hypothesis.

In the estimation of the regression model, it appears that some of the macro-economic variables are too highly intercorrelated to allow precise analysis of their individual effects. The correlation coefficient between the monthly change in our GDP proxy and the monthly change in stock prices is 0.63. The two regressors show the symptoms of multicollinearity: coefficient estimates of the two variables have high standard errors, which can produce wide swings in response to small changes in the sample. One remedy suggested by Greene (1993) is to drop one of the variables suspected of causing the problem from the regression. Further specification analysis reveals that the GDP regressor induces higher multicollinearity among all explanatory variables than the stock price index. We therefore drop the GDP proxy from the regression.

Figure 1 shows the annual bank failure rate—that is the number of bank failures as a percentage of the total number of banks—from 1865 till 1940. The bank failure rate is rather stable from 1865 till 1920, apart from occasional banking panics. Examples of the various banking panics in this period are the crises of 1873, 1884 and 1893 (see, for example, Sprague, 1910). The bank failure rate starts to increase in the 1920s, cumulating in multiple bank failures in 1930-33. Testing for structural change, we divide the overall sample into two sub-sample periods: 1880-1919 and 1920-1936 (most of our macro-economic data series start in January 1877 and stop in January 1937). We conduct the likelihood ratio test for structural change on the model before and after 1920. The likelihood ratio test is based on the maximum likelihood method (Hamilton, 1994).

Figure 1: Annual bank failure rate, 1865-1940



To perform the test we define a dummy variable, which is zero for each month until December 1919 and one for each month from January 1920 onwards. In the restricted version of the model, each pre-1920 coefficient is imposed to be equal to the corresponding post-1920 coefficient. The unrestricted version allows for different behaviour in the post-1920 period. Column 1 of Table 2 reports the restricted version and column 2 the unrestricted version of the model. It can be seen that for most variables, there is a significant change of slope indicating a structural break.[10] The likelihood ratio test statistic is computed as two times the difference between the log-likelihood for the unrestricted version and the log-likelihood for the restricted version: $2[\ln L_{UR} - \ln L_R] \sim\chi^2(m)$. The relevant value in our case is: 285.36. As $\chi^2(7,.99) = 18.48$, we can clearly reject the null hypothesis of no structural change.

[10] The post-1920 slope coefficients for each variable are found by adding the overall coefficient and the dummy coefficient in the unrestricted model. For stock prices, for example, the coefficient in the 1920-1936 period is -0.307 (= -0.652 + 0.345).

Table 2: Test for structural change in number of bank failures, 1880-1936

Explanatory variables	*Restricted*	*Unrestricted*
CONSTANT	0.431***	0.109**
	(26.92)	(2.48)
ΔSP_t	-0.092	-0.652*
	(1.19)	(1.94)
ΔP_t	-1.509***	-4.431***
	(4.30)	(3.30)
ΔR_t	0.022**	0.049
	(2.01)	(1.54)
BF_{t-1}	0.291***	0.145***
	(17.23)	(6.34)
BF_{t-2}	0.289***	0.175***
	(17.05)	(6.55)
BF_{t-3}	0.162***	0.077***
	(10.11)	(3.09)
DUMMY * CONSTANT		0.266***
		(3.58)
DUMMY * ΔSP_t		0.345
		(0.99)
DUMMY * ΔP_t		4.518***
		(3.22)
DUMMY * ΔR_t		-0.082**
		(2.20)
DUMMY * BF_{t-1}		0.260***
		(7.78)
DUMMY * BF_{t-2}		0.134***
		(3.62)
DUMMY * BF_{t-3}		0.033
		(0.93)
Log-likelihood	-1575.08	-1432.40

DUMMY = 0 for 1880-1919 and DUMMY = 1 for 1920-1936
Maximum likelihood estimates of coefficients
t-statistics in parentheses (absolute values)
*** significant at 1% level
** significant at 5% level
* significant at 10% level

The empirical results are presented in Table 3. Starting with the first period from 1880 to 1919, all coefficients have the expected sign. The coefficient for stock prices (ΔSP) is negative—a fall in stock prices generates more bank failures—and

Table 3: Regressions of number of bank failures, 1880-1936

Explanatory variables	*1880-1919*	*1920-1936*
CONSTANT	0.109***	0.374***
	(2.66)	(6.54)
ΔSP_t	-0.645*	-0.307***
	(1.90)	(3.24)
ΔP_t	-4.467***	0.086
	(3.21)	(0.20)
ΔR_t	0.049	-0.033*
	(1.58)	(1.77)
BF_{t-1}	0.146***	0.404***
	(7.50)	(15.64)
BF_{t-2}	0.174***	0.307***
	(7.14)	(11.40)
BF_{t-3}	0.077***	0.113***
	(3.09)	(4.50)
Log-likelihood	-658.11	-774.50
Pseudo-R^2	0.17	0.59
Ljung-Box (13 lags)	16.09	13.63

Maximum likelihood estimates of coefficients
t-statistics in parentheses (absolute values)
*** significant at 1% level
** significant at 5% level
* significant at 10% level

The pseudo-R^2 is computed as: $1 - \ln L(\Omega) / \ln L(\omega)$, where $\ln L(\Omega)$ is the value of the log-likelihood function evaluated at the maximum likelihood estimates and $\ln L(\omega)$ is the maximum value of the likelihood function under the hypothesis that the coefficients of all regressors are zero.

The Ljung-Box statistic for serial correlation is calculated for 13 lags to allow for seasonal influences. The statistic is distributed as: $\chi^2(13)$. The reported statistic in both periods is below the critical value of 19.88 at the 90% level, so there is no evidence of serial correlation.

is significant at the 10% level. The rate of inflation (ΔP), i.e. the first difference in prices, is negatively correlated (at the 1% level of significance) with the bank failure rate. During periods of (unexpected) increasing inflation the burden of debt diminishes for a bank's borrowers, while it rises in times of decreasing inflation or deflation.[11] The impact of interest rates (ΔR) is close to the 10% significance level ($p = 0.11$): an increase in short-term rates raises funding costs for banks and causes a higher bank failure rate. We have run the regressions with different lags for the macro-economic variables, but the contemporaneous impact of the variables appears to be the strongest.

After controlling for macro-economic influences, we still find a strong form of dependency in the bank failure data. The coefficients of the lagged number of bank failures (for 1 to 3 lags) are all significant at the 1% level. The persistence of bank failures is thus up to three months. In our application of the autoregressive Poisson model, γ_1 can be interpreted as the elasticity of the current number of bank failures, BF_t, with respect to the number of failures in the previous month, BF_{t-1}. As displayed in Table 3, the elasticities with respect to BF_{t-1}, BF_{t-2}, and BF_{t-3} are 0.146, 0.174, and 0.077, respectively. A 1% increase in the number of bank failures in the previous month will lead to a 0.15% rise in the number of failures this month, *ceteris paribus*. The combined impact of a 1% increase in the number of failures in each of the three preceding months is a 0.40% rise in the current number of failures.

The results for the second period, 1920-1936, are also reported in Table 3. Again, as expected, the number of bank failures is negatively correlated with stock prices at the 1% level of significance. The correlation coefficient of inflation has a positive sign, but is not significant ($t = 0.20$). The relationship between bank failures and interest rates is negative, which is surprising. Lower funding costs (in the form of lower short term interest rates) generate more bank failures, and vice versa. However, the coefficient is only significant at the 10% level. The overall assessment is that the explanatory power of macro-economic factors in the second period (1920-1936) is less strong than in the first period (1880-1919).

On the other hand, bank failures showed more dependency during the Great Depression than in the first period. This indicates that the multiple bank failures during the 1930s are more driven by the spread of contagion than by macro-economic factors. The elasticities of the current number of bank failures with respect to the number of failures in each of the three preceding months is 0.404, 0.307, and 0.113, respectively (with all three coefficients significant at the 1% level). The combined impact of a 1% increase in the number of failures in each of the three preceding months is a 0.83% rise in the current number of failures. The contagion effect in the second period (0.83%) is thus about twice as much as in the first period (0.40%).

To shed light on the 'too big to fail' problem, we also examine in both periods whether the lagged size of the failed banks (measured by the amount of outstanding deposits at the date of failure) in addition to the lagged number of failed banks has any impact on the failure rate. Consistent with Davutyan (1989), we do

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[11] This result is consistent with Goodhart (1995) and Heffernan (1995). Goodhart reports that bank failures are high when asset (especially housing and property) prices have peaked, and have started to decline, and when the rate of inflation of current flow prices is starting to decline.

not find a significant result for the size variable.[12] It should be noted, however, that there are missing values in the data on outstanding deposits which are estimated by data on paid-in capital of failing banks (see the Appendix). The used proxy for size may therefore not be very reliable.

Reviewing our results, we conclude that macro-economic variables have explanatory power in our model of bank failure. Furthermore, the results indicate that bank failures are dependent, providing support for the lender of last resort role performed by the central bank (e.g. Goodhart, 1987). The social cost of a bank failure (i.e. the potential contagious effects) can be higher than the private cost, justifying lender of last resort intervention. Put differently, it may be cheaper in certain cases to stop the initial failure upfront rather than to let the contagion spread unfettered.

Linking our results to earlier studies, Grossman (1993) reports a smaller contagion effect than we do. Grossman uses OLS regressions to assess the contagion effect under the National Banking System. Using quarterly data on bank failures from 1875 to 1914, he finds a coefficient on lagged bank failures in the failure equation of 0.260. The current number of failures will rise by 0.26% in response to a 1% increase in the number of failures in the previous quarter. To compare our results with those of Grossman, we have repeated our MLE estimations for the 1878-1914 period. The respective parameter estimates of γ_1, γ_2, and γ_3 are 0.142, 0.178, and 0.058. The current number of failures will rise by 0.38% in response to a 1% increase in the number of failures in each of the three preceding months. The higher frequency of our data (monthly) enables us to identify more clearly the contagion effect.[13] In addition, the use of OLS regressions to analyse discrete data may lead to mis-specifications (see above).

Another recent study (Hasan and Dwyer, 1994) examines bank contagion by estimating probit equations for bank closings during the Free Banking Era from 1837 till 1863. Analysing periods with large numbers of banks closing, Hasan and Dwyer find evidence of bank contagion in the state of New York during the crises of 1841-42 (significant at the 10% level) and 1854 (at the 5% level). But they do not observe contagion effects during the 1854 crisis in Indiana and the 1861 crisis in Wisconsin. The Free Banking Period ended with the introduction of the National Currency Act in 1863 and thus precedes our period of analysis, for the National Banking System was established in 1864.

Finally, a further test could be designed to investigate whether banking is 'special' with regard to contagion risk. Contrasting data on business failures and bank failures, it can be analysed whether business failures show less dependency, i.e. gamma in equation (9) is lower than for banking and, perhaps, close to zero. This procedure would allow us to test whether the risk of contagion is more

[12] Analysing a dataset of US bank failures from 1947 till 1986, Davutyan (1989) reports that the coefficient for size (also measured by deposits in failed banks) is always insignificant.

[13] It should be noted that we use several macro-economic variables to measure common factors explaining bank failures, while Grossman uses only one variable (GDP). If anything, our estimated contagion effect should be smaller than that of Grossman, *ceteris paribus*.

prominent in banking than in other industries. Unfortunately, monthly data on business failures are difficult to obtain for our reference period (1880-1936). This is an area for future research.

4 Concluding remarks

In this paper, we develop a model to measure possible contagion risk, which is defined as the risk that an initial bank failure may spill over to the rest of the banking industry and cause further bank failures. An autoregressive Poisson model is used to deal explicitly with the count nature of bank failure data. Although most earlier empirical studies (e.g. Aharony and Swary, 1983; Swary, 1986) find little evidence of contagion, this evidence is not conclusive as some of these US studies examine possible contagious effects during periods in which the Federal Reserve acted as lender of last resort. To avoid this pitfall, we use data from the US National Banking System, which was founded some fifty years before the establishment of the Federal Reserve.

The empirical results indicate that bank failures are dependent after controlling for macro-economic influences. These results are consistent with the existence of contagion risk in banking. An initial failure could generate further failures without intervention by the authorities. The results are compatible with recent studies on contagion during the pre-Federal Reserve years (e.g. Grossman, 1993; Hasan and Dwyer, 1994). In spite of including more macro-economic variables to control for common factors than Grossman, we find stronger contagion effects. First, our methodology of Poisson regressions is better suited to deal with discrete data, such as bank failures, than Grossman's OLS regressions. Second, the use of monthly, instead of quarterly, data allows us to capture more precisely possible effects of contagion, which is a fast-moving phenomenon.

Our empirical findings underpin the view that lender of last resort assistance to individual banks may be justified *in certain circumstances* to prevent the potential contagious effects of bank failures (e.g. Solow, 1982; Goodhart, 1987). The central bank as lender of last resort should, however, not preserve all banks from failure, but should only prevent those failures that are expected to have a systemic impact. Furthermore, the banking sector that receives liquidity support may need to be regulated and supervised to contain the moral hazard effects of such lender of last resort intervention.

Data appendix

<u>Bank failures</u>: In our empirical study of contagion risk in Section 3, we examine the period from 1865 till 1940. Data on bank failures are taken from various issues of the *Annual Report* of the Comptroller of the Currency. The 1931 *Annual Report* (Table 46, p.311) contains a survey of all failures from the inception of the National Banking System up to 1930. The date of each failure and the amount of

outstanding deposits at the date of failure are compiled. There were, however, about 10% missing values in the data on outstanding deposits. The missing values are estimated by examining the paid-in capital of a failing bank. It should be noted that paid-in capital is a poor proxy for the size of a bank, as banks that expand do not always increase their capital base accordingly. The total number of banks and total amount of deposits are taken from *Banking and Monetary Statistics, 1914-1941* (Board of Governors of the Federal Reserve System, 1943, Table 4, p.20-1).

Macro-economic variables: The level of real output is proxied by pig iron production in the US. Monthly data on pig iron production (in thousands of gross tons) from Jan. 1877 till Jan. 1937 are published in *The Movements of Interest Rates, Bond Yields and Stock Prices in the United States since 1856* (Macaulay, 1938, Table 27, column 4, p.A252-70). Stock prices are measured by a value weighted index of stock prices on the New York Stock Exchange with cash dividends reinvested. The data before 1871 are not meaningful and comprise mainly railroad stocks. The monthly series on stock prices covers 1871-1937 and is published in *Common Stock Indices, 1871-1937* (Cowles, 1938, Series C-1, p.167-9). Prices are measured by Carl Snyder's Index of General Price Level, from Jan. 1875 till Jan. 1937 (Macaulay, 1938, Table 27, column 5, p.A252-70). The short-term interest rate is the commercial paper rate in New York City. From 1865 till 1923, the CP rate is the 'choice 60-90 day two name paper,' and from 1924 till Jan 1937 the CP rate is the '4 to 6 month prime double and single name paper' (Macaulay, 1938, Table 10, column 3, p.A141-61).

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