Financial Efficiency and Aggregate Fluctuations: An Exploration

by Joseph G. Haubrich

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Introduction

Banks may both initiate and propagate business cycle fluctuations. For example, recent controversy has arisen over the role that banks' loan decisions may have played in the initiation of economic downturns. However, once such a downturn has begun, business performance influences bank profits and eventually may influence loans.

A natural question is whether banks play an independent role in business cycle movements. One possibility is that technological advances specific to banking influence the initiation or continuation of business cycles. Although economists have studied the macroeconomic impact of broad technological advances, they have not yet focused on the impact of the obvious recent gains in banking technology.

In this paper, I explore the possible link between financial efficiency and macroeconomic fluctuations. I present a two-sector real business cycle model in which there are technological shocks specific to the banking sector. (For a discussion of these shocks, see box 1.) I then test the model's empirical implications, which are interpreted with the concept of cointegration. Although these implications have not yet been investigated by others, I follow Mitchell (1913) by examining linear combinations of banking variables. This approach is linked to the cointegration techniques utilized. Specifically, I test whether a common stochastic trend exists between banking variables and industrial production, or whether the two are subject to distinct stochastic trends. This is equivalent to testing for the absence of cointegration between the banking variables and industrial production. Such a finding would imply that the banking sector exerts independent influence on long-run output.

Other researchers have begun to consider roles for financial efficiency. On the theoretical side, King and Plosser (1984) mention financial efficiency, but do not imbed a role for it in the solution of their model. Greenwood and Williamson (1989) develop a model with an explicit but constant term for financial efficiency. On the empirical side, Norrbin and Schlagenhauf (1988) present a highly disaggregated model, but one that does not explicitly consider technological change. They also discuss employment rather than output in the financial sector, and use a different time period (1954–1984). Corradi, Galeotti, and Rovelli (1990) look at the long-run relations among bank variables in Italy without considering the aggregate economy. Scotese (1990), in unpublished work, BOX 1

Some Examples of Bank Innovations

As an antidote to the rather abstract theory and empirical work in the rest of the paper, it may be useful to consider some examples of the sort of shocks I have in mind. Banks employ many resources in processing transactions, in maintaining the payments system, and in screening and monitoring lenders and borrowers. Advanced information technology has reduced these costs and created new products. In the period covered by the study (1923–1978), some efficiency gains stem from outside technological advances, others are unique to banks, and still others are unclear.

Even in cases where outside technology increases financial efficiency — Scotch Tape in the 1930s, or calculators and electric typewriters in the 1940s — the specific uses and total gain can vary by industry. For example, using radio and television to disseminate information has meant very different things to the banking, the soap, and the fashion industries.

Other improvements seem more specific to banks. These include innovations like money orders and warehouse receipts to collateralize loans in the 1930s; drive-up windows, account numbers, and check routing numbers in the 1940s; and central information files in the 1960s. Yet, not all "breakthroughs" look so stunning in retrospect. In the 1920s, for instance, banks placed a strong emphasis on graphology, using handwriting analysis to screen employees and customers.

Today, the contribution of computer technology with image processing enables payments, credits, and debits to be made more cheaply, easily, and quickly, especially far from home. Banks can use this technology to calculate and adjust exposure and interest-rate risk. As daily processing becomes commonplace, on-line transaction processing becomes more frequent. Banks have also reduced the costs of monitoring and screening and have automated the process of sending out warning letters. Data bases make all customer accounts accessible, easing credit-risk analysis and targeted advertising.

One recent innovation, for example, is the "super-smart card." Resembling a credit card, it fits easily into a wallet and contains memory, a processor, keyboard, screen, calculator, and clock. Debits and credits can be made merely by punching a secret code, making transactions quicker than is possible with current credit and debit cards. More secure than an ATM card, the super-smart card also reduces costs by eliminating the need for point-of-sale terminals to be connected to a central location. It holds the promise of inducing even more radical changes: Pocket currency could pay interest, or even float against that of other banks. Such capabilities have the Japanese Ministry of Finance worried about losing control of the nation's money supply (Abrahams [1988]).

One indicator of technology's influence is the substantial consulting industry that banks support to help them manage extensive technological change. Estimates suggest that the largest of the 25 consulting firms profiled in a recent issue of *American Banker* collects $400 million annually from bank technology consulting alone (Gullo [1991]).

examines the relation between economic growth and financial innovation, but models technological changes differently and examines fewer banking variables than I do. She also uses quarterly data from 1959 to 1990, whereas I use a longer data series (1923–1978.)

The remainder of the paper proceeds as follows. Section I presents the simple model and explains why technological shocks imply no cointegration between banking and real variables. Section II describes the data, the method of testing, and the test results. Contrary to the prediction of the model, banking and real variables are cointegrated. Section II further explores the interaction with vector autoregression methods, and section III concludes.

I. Lessons from a Simple Model

To consider the effects of shocks to financial efficiency, I begin with a dynamic stochastic model: a two-sector real business cycle model with technological shocks to both sectors. This two-industry version of the Long and Plosser (1983) model has testable predictions and indicates the progress that can be made by treating banks like any other industry. It retains a somewhat traditional flavor, however, because it places transactions services directly into both the utility function and the production function.

Consider a model economy with two goods and a representative agent who chooses a production and consumption plan. The infinitely lived agent has resources, technologies, and tastes similar to those in Long and Plosser, and has a lifetime utility function of $U = \Sigma\beta^t u(C_t, Z_t)$, where C_t is a 2x1 vector denoting period t consumption of goods (C_G) and banking services (C_B). Z_t measures the quantity of leisure consumed in period t. Each period's utility function, $u(C_t, Z_t)$, is given by

$$(1) \quad u(C_t, Z_t) = \theta_0 lnZ_t + \theta_G\, lnC_{Gt} + \theta_B\, lnC_{Bt}.$$

The agents face two resource constraints: Total time H may be spent at work or at leisure, and output Y_t may be consumed or invested.

$$(2) \quad Z_t + L_{Gt} + L_{Bt} = H$$

$$(3) \quad C_{jt} + X_{Gjt} + X_{Bjt} = Y_{jt}.$$

Thus, labor can be divided between producing transactions services in the banking sector or output in the goods sector, just as the goods (output and banking services) can be consumed or invested. X_{ij} denotes the amount of good j invested in process i. For example, X_{GB} is the amount of banking services used to produce the manufactured good. Output is determined by Cobb–Douglas (1928) technology with a random productivity shock.

$$(4)\qquad Y_{G,t+1} = \lambda_{G,t+1}\, L^{b_G}_{Gt}\, (X_{GG})^{a_{GG}}\, (X_{GB})^{a_{GB}}$$

$$Y_{B,t+1} = \lambda_{B,t+1}\, L^{b_B}_{Bt}\, (X_{BG})^{a_{BG}}\, (X_{BB})^{a_{BB}},$$

where $\lambda_{i,\,t+1}$ is a random productivity shock whose value is realized at the beginning of period $t+1$, and the exponents are positive constants with $b_i + a_{iB} + a_{iG} = 1$. For future reference, define the matrix of input-output coefficients a_{ij} to be matrix A. Because the state of the economy in each period is fully specified by that period's output and productivity shock, it is useful to denote that state vector $S_t = [Y_t'\ \lambda_t']$. To further simplify the problem, all commodities are perishable, and capital depreciates at a 100 percent rate.

Subject to the production function and resource constraints in equations (2), (3), and (4), the agent maximizes expected lifetime utility. This problem maps naturally into a dynamic programming formulation with a value function $V(S_t)$ and optimality conditions. By assuming log utility, it is straightforward to discover and verify the form of $V(S)$. Thus, the first-order conditions for the optimality equation specify the chosen quantities of consumption, work effort, investment, and leisure. Because they are just special cases of Long and Plosser (1983), the first-order conditions are not reported here.

Of greater interest is the time series of output, which can be calculated from the production function and the decision rules for consumption and investment. Letting $y_t = lnY_t$ and $\eta_t = ln\lambda_t$ and k be an appropriate vector of constants, quantity dynamics come from the difference equation

$$(5)\qquad y_{t+1} = Ay_t + k + \eta_{t+1}.$$

Since the focus is on technological change and increasing efficiency, a particular process for η can be chosen in order to capture the accumulation of knowledge. Thus, it seems appropriate to model λ_t as a multiplicative random walk:

$$(6)\qquad \lambda_{i,\,t+1} = \lambda_{i,\,t}\, e^{\upsilon_{t+1}},$$

which implies

$$(7)\qquad \eta_{t+1} = \eta_t + \upsilon_{t+1}.$$

This means that the difference equation for output, (6), can be expressed as

$$(8)\qquad \Delta y_{t+1} = \Delta A y_t + \upsilon_{t+1}.$$

Expanding this leads to

$$(9)\qquad \begin{pmatrix} \Delta y_{G,t+1} \\ \Delta y_{B,t+1} \end{pmatrix} = \begin{pmatrix} a_{GG} & a_{GB} \\ a_{BG} & a_{BB} \end{pmatrix} \begin{pmatrix} \Delta y_{Gt} \\ \Delta y_{Bt} \end{pmatrix} + \begin{pmatrix} \upsilon_{G,t+1} \\ \upsilon_{B,t+1} \end{pmatrix}.$$

This representation has several notable features. First, innovations in one industry will affect the other. Second, the A matrix provides rich dynamics for both individual series and comovements. Even this simple approach captures two essential points: (1) banks complicate the transmission of aggregate disturbances, and (2) banking changes serve as a *source* of such disturbances.

Econometric Modeling

Exploration of the empirical implications of equation (9) requires introducing some concepts from time-series analysis. The objective is to assess the connection between the banking sector y_B and the industrial sector y_G. If shocks have a permanent effect on output, as equation (9) assumes, traditional econometric methods such as correlation or regression become inappropriate. Those methods can miss existing relations and spuriously uncover nonexisting ones.[1] Fortunately, natural analogues exist in the notions of common trends and cointegration.

As described in Engle and Granger (1987) and Box and Tiao (1977), cointegration is a restriction on how far two series may wander apart. For example, two unrelated random walk series, such as GNP and quasar light intensity, should drift far afield. Two related series, such as income (I) and consumption (C), may each individually be a random walk, but will never drift very far apart. Engle and Granger formalize this with the concept of cointegration, where a linear combination (for example, I – C) is stationary. Stock and Watson (1988) describe cointegrated series as having "common stochastic

■ 1 More formally, with a random-walk error term, estimated regression coefficients do not have finite moments and may be inconsistent (Plosser and Schwert [1978]). Informally, the high autocorrelation of the errors means that if the first error is positive, the following several errors will also be positive, making the estimated regression line lie above the "true" regression line (Theil [1971], section 6.3). With the pronounced tendency of a random walk to wander, the differences could be substantial.

trends." The same underlying random walk drives both series, though each will have noise on top of the random walk.

In terms of this paper's model, banking and output are cointegrated if each is integrated — so that shocks become embedded in the series — but some combination of the variables is stationary. I interpret a cointegrating relationship as evidence that the same unobservable force drives both series. It is also possible that each series may be integrated, while the two series are not cointegrated. In this case, shocks tend to have a permanent effect on the series, but there is no evidence that the same shock affects both series. Finally, it may be that neither series is integrated.

More generally, if X_t is an nx1 time-series variable, with each element first-difference stationary, X_t is cointegrated (of order [1,1]) if at least one linear combination of X_t is stationary. Expressing the change in X_t as a moving average, I get

$$(10) \quad \Delta X_t = \mu + C(L)\,\varepsilon_t,$$

where μ is an nx1 vector of means; $C(L) = \sum_{i=0}^{\infty} C_i L^i$ with each C_i nxn; ε_t is nx1 and independent and identically distributed; and $\Delta = 1 - L$, with L the lag operator. Cointegration places restrictions on $C(L)$ (Stock and Watson [1988]). Thus, if X_t is cointegrated, the matrix C(1) will have rank $k < n$, with $r = n - k$ denoting the number of cointegrating vectors. Equivalently, there will exist an nxr matrix B such that $B'\mu = 0$ and $B'C(L) = 0$. The columns of B are termed the cointegrating vectors (Engle and Granger [1987]).

The two properties of the B matrix, $B'\mu = 0$ and $B'C(L) = 0$, summarize the meaning of cointegration. The first indicates that the expected net impact of the shock on some combination of the series is zero. The second means that the long-run impact on that same combination is zero. This is the essence of cointegration: Although shocks have a permanent effect on the level of the integrated series, they have only a transient effect on some combination of the series.

With this machinery in hand, I rearrange equation (8) as

$$(11) \quad (I - AL)(\Delta y_{t+1}) = \upsilon_{t+1}.$$

Making a standard assumption to rule out explosive growth, the matrix I – AL inverts (the Hawkins–Simon [1949] conditions), yielding

$$(12) \quad \Delta y_{t+1} = (I - AL)^{-1}\,\upsilon_{t+1}.$$

Assuming invertibility assumes away cointegration: To invert, the matrix must have full rank. In the standard case, then, we do not expect to find cointegration. Another interpretation emphasizes that equation (12) has two stochastic trends, ruling out the single, common trend that is the sine qua non of cointegration.

Cointegration can occur in special cases. Consider a degenerate version of equation (5) where the same permanent output shock affects banking and industry:

$$(13) \quad y_{Gt+1} = a_{GG}\, y_{Gt} + \eta_t + \upsilon_{t+1}$$
$$y_{Bt+1} = a_{BG}\, y_{Gt} + \eta_t.$$

Here, the stationary linear combination is $y_{Gt+1} - y_{Bt+1}$. This example highlights the intuition behind identifying cointegration with a common stochastic trend. The same stochastic productivity trend drives both industrial output and banking output. Hence, single-sector models, such as in King, Plosser, Stock, and Watson (1991), imply cointegration between variables. Multisector models, such as the one considered here, with each sector driven by its own technology shock, imply the opposite. Testing for cointegration determines whether the stochastic trend is common.

Neither assumption obviously is a better approximation of reality. Long and Plosser (1983, p. 61) assume independent random-walk shocks to "...avoid comovements arising from common shocks." If one contemplates improved ways of working, of organizing and running a firm, and of adapting existing science to create further specialized breakthroughs, it makes sense that production shocks may be relatively independent. On the other hand, the development of transistors, computers, and phones helped all sectors to increase productivity, so it makes sense that productivity may have a substantial common component.

This simple model implies a sharp prediction: Banking should not be cointegrated with aggregate output. This is somewhat counterintuitive, since other approaches (such as King et al.) suggest that important relations exist if variables are cointegrated. Here, financial efficiency matters in the long run only if no common trend links banks and the economy. Finding otherwise means rejecting the model.

II. Data Analysis

Implementing the tests suggested in section I requires several decisions about data and specifi-

FIGURE 1

Log of Real Loans

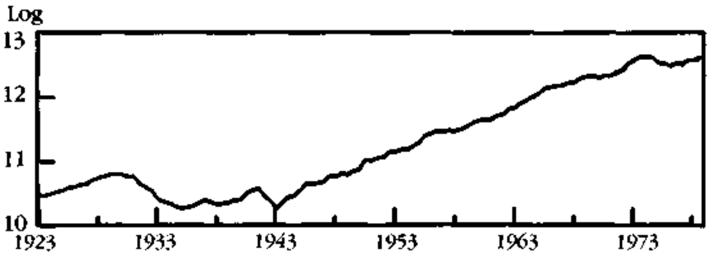


FIGURE 2

Log of Real Deposits

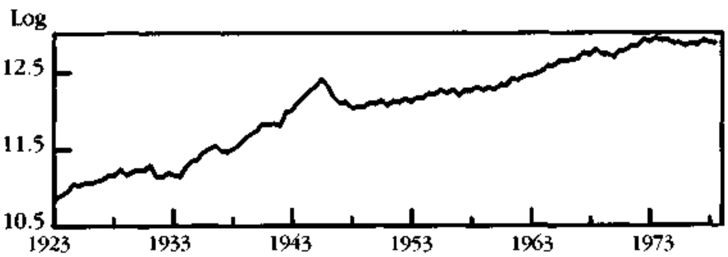


FIGURE 3

Log of Real Reserves

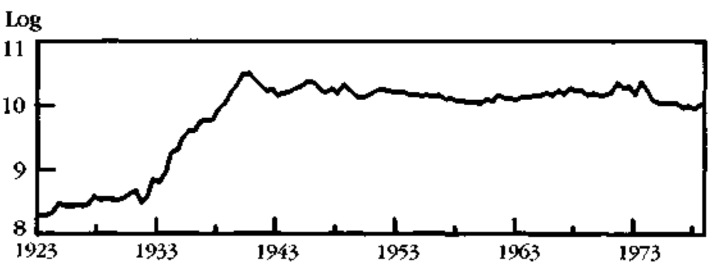
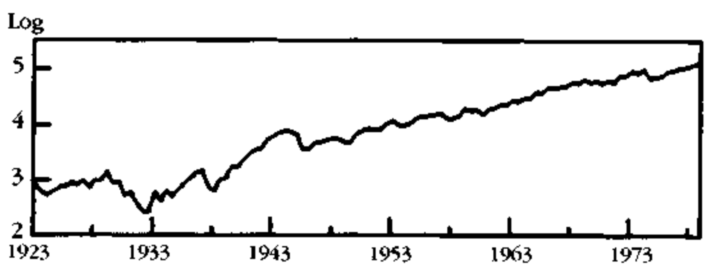


FIGURE 4

Log of Industrial Production



SOURCE: Author's calculations based on data from the Board of Governors of the Federal Reserve System and from U.S. Department of Labor, Bureau of Labor Statistics.

cations. I take as my guide the work of Wesley Clair Mitchell (1913), who early in the century commented on the comovements of loans, deposits, and reserves within the business cycle. He stressed that several combinations, such as the loan-to-deposit ratio, track the cycle more closely than do individual series. This suggests a stationary linear combination, and ties in naturally with the cointegration framework proposed above. I first test for cointegration among various measures of bank output and industrial production with the methods of Johansen (1991) and Johansen and Juselius (1989). To obtain a richer picture of the dynamic interactions, I then examine the vector representation of the model.

Following Mitchell and using loans, deposits, and reserves is not the only way to measure the output of the banking industry (for other methods, see Fixler and Zieschang [1991]). However, using financial variables is a sensible way to consider output when the Modigliani–Miller (1958) theorem does not hold. That is, real effects can depend on more than net worth, total wages, or other factor payments; the asset-liability structure also matters.

Because cointegration is a long-run property, I use semiannual data from 1923 to 1978, which represents a longer, if somewhat sparser, data set than the usual postwar quarterly series. This covers the years for which the Federal Reserve and the Comptroller of the Currency reported data on Federal Reserve member banks (all national banks and state member banks). The underlying figures are from the Federal Financial Institutions Examination Council's Reports of Condition and Income (call reports), which until recently were tabulated only twice a year. After 1978, changes in the membership of the Federal Reserve System made the numbers less representative, and reporting procedures made the data more difficult to obtain. The figures for reserves, deposits, and loans are from *Banking and Monetary Statistics 1914–1941* and *1939–1970*, as well as from various issues of the *Federal Reserve Bulletin*. Details about revising the series for consistency are in section 2 of the 1976 edition. Note that these are stock variables, reported at the end of June and December. The Consumer Price Index for all urban consumers (CPI-U) is used for deflating purposes, and aggregate output is measured by the monthly Index of Industrial Production. Both were obtained from the DRI/McGraw-Hill U.S. data base for the month of the call report. All numbers are not seasonally adjusted.

Before moving to the more formal statistical work, it is worthwhile to examine the data directly. Figures 1–6 provide such an overview. Figures 1, 2, and 3 plot the log of real loans,

TABLE 1

Growth of Banking Variables, 1923–1978 (Millions of dollars)

	1923	1939	1952	1978
Reserves				
Nominal	1,898	11,604	19,810	31,150
Real	10,970	82,890	74,190	46,010
% of GNP	2.2	1.27	0.57	0.14
Deposits				
Nominal	28,507	49,340	147,527	716,300
Real	164,780	352,430	552,540	1,058,100
% of GNP	34.1	54.3	42.3	33.1
Loans				
Nominal	18,892	13,962	55,034	558,300
Real	108,910	99,730	206,120	824,670
% of GNP	22.5	15.4	15.8	25.8

SOURCES: Board of Governors of the Federal Reserve System (1943, 1976), Gordon (1986, appendix B), and Wharton Econometric Forecasting Associates.

FIGURE 5

Log of Deposit/Loan Ratio

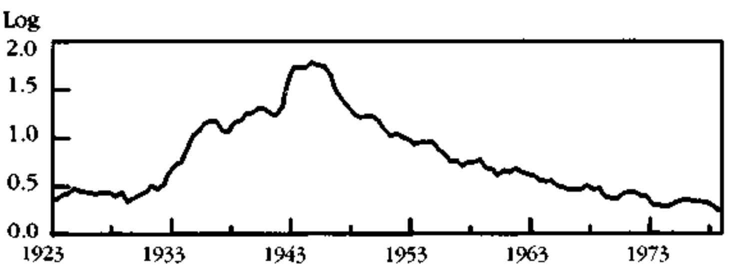
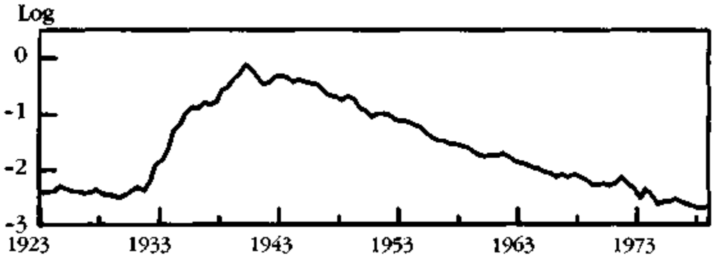


FIGURE 6

Log of Reserves/Loan Ratio



SOURCE: Author's calculations based on data from the Board of Governors of the Federal Reserve System and from U.S. Department of Labor, Bureau of Labor Statistics.

deposits, and reserves. Note the major influences of the Great Depression and World War II years. Figure 4 plots industrial production, and figures 5 and 6 show some combinations suggested by Mitchell (1913). Here, note the large relative increase in reserves during the Depression and the surge in the deposit/loan ratio during World War II. Figure 7 plots the ratio of loans to industrial production, a rough measure of the relative size of the banking sector. Table 1 provides another view of this growth, comparing nominal levels, real levels, and percent of GNP for reserves, deposits, and loans for four different years.

Because looking for cointegration makes sense only for integrated variables, I first test for the presence of unit roots in the individual series. Inference about unit roots can be a delicate, even controversial, matter. Individual tests make different assumptions and offer different degrees of robustness to deviations from those assumptions. However, if a variety of tests agree, more confidence can be placed in the results. This section uses the Dickey–Fuller (1979) test and the Phillips–Perron (1988) test, both with and without trends.

The Dickey–Fuller test assumes a time series of the form

$$(14) \quad Y_t = \alpha + \beta t + \rho\, Y_{t-1} + \varepsilon_t .$$

The test is a t-test or "normalized bias" test for $\rho = 1$. Under the null hypothesis that $\rho = 1$, the test statistic has a nonstandard distribution and requires the use of Dickey–Fuller tables. The test can be run with or without the trend term βt.

Phillips and Perron (1988) allow more complicated error terms by using the residual autocorrelations from a rearrangement of equation (14) to adjust the Dickey–Fuller statistics. The Phillips–Perron statistics have the same limiting distributions as those of Dickey–Fuller, so the same tables can be used in the tests.

Table 2, panel A reports the results of the tests with no trend. At the 5 percent level, I accept the null hypothesis of a unit root in the series in every case except for reserves. Even for reserves, I accept the null hypothesis at the 1 percent significance level. A comforting feature is that the Dickey–Fuller and Phillips–Perron tests generally agree.

Table 2, panel B reports the results of the tests with a trend. Here, the findings argue for rejecting the null hypothesis of a unit root in both industrial production and deposits. Again, the Dickey–Fuller and Phillips–Perron tests concur.

TABLE 2

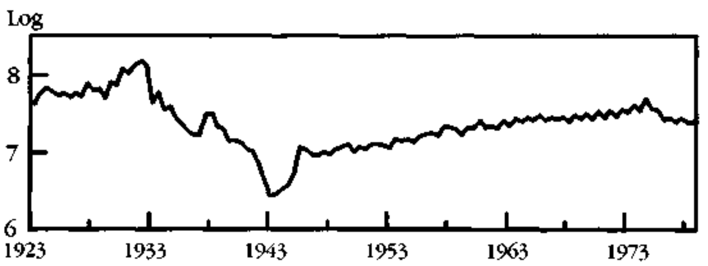
Unit Root Tests

	Dickey-Fuller T(ρ-1) test T	Critical Values No. of Observations = 100			Phillips-Perron Test T (4 lags)
A. No trend case		1%	5%	10%	
Industrial production	−0.35	3.51	2.89	2.58	−0.21
Loans	0.79				0.58
Deposits	−1.57				−1.61
Reserves	−3.46				−3.74
B. Trend case		1%	5%	10%	
Industrial production	−18.50	3.51	2.89	2.58	−19.93
Loans	−2.62				−3.81
Deposits	−8.10				−9.78
Reserves	−2.07				−2.50

NOTE: *All variables are real, logs, and not seasonally adjusted.*
SOURCE: Author's calculations using the RATS (DFUNIT, PPUNIT) program from Estima.

FIGURE 7

Log of Loans/ Industrial Production Ratio



SOURCE: Author's calculations based on data from the Board of Governors of the Federal Reserve System and from U.S. Department of Labor, Bureau of Labor Statistics.

Tests for Cointegration

Although the results are sensitive to the inclusion of trends, I provisionally continue with the next step of the exercise — testing for cointegration — for two reasons. First, given the ambiguous results of the unit root tests, if I hold as a null hypothesis that the series are integrated, I have not decisively rejected that view. Second, Schwert (1989) shows that when the time series possess a moving-average component (as many economic time series are thought to do), the unit root tests used above reject unit roots in favor of stationarity too often.[2]

The Johansen approach to cointegration (based on Johansen [1991] and Johansen and Juselius [1989]) uses a maximum-likelihood estimation procedure. This procedure treats the error-correction representation of the cointegrated time series as a reduced rank regression.

The procedure first regresses ΔY_t on ΔY_{t-1}, $\Delta Y_{t-2}, \ldots, \Delta Y_{t-p+1}$ to obtain residuals r_{0t} and then regresses Y_{t-1} on the same lags to obtain residuals r_{1t}. The reduced rank regression is then

$$(15) \quad r_{0t} = \Gamma \alpha' r_{1t} + \varepsilon_t .$$

Testing for cointegration means testing for the rank of the matrix $A = \Gamma \alpha'$. This can be done using a likelihood ratio statistic. Johansen extends this approach to test hypotheses about the cointegrating vector and the form of the multivariate model.

Table 3 reports the results of the Johansen trace test for the number of cointegrating vectors, testing whether there are zero, one or fewer, two or fewer, or three or fewer common trends. The table also lists the distribution of the trace statistic, taken from table D.1 of Johansen and Juselius (1989).

The statistics in table 3 indicate that we can reject the null hypothesis of no cointegrating vectors, but that we cannot reject the hypotheses that the

2 The unit root tests deserve some discussion of their ability to distinguish between the two hypotheses. If the trend is omitted, I fail to reject the null of integration. If the trend is included, I do reject the null (for two series). Unfortunately, the test without a trend is inconsistent against the alternative of a trend, which is the alternative of interest (that is, even with an infinite amount of data it can give the wrong answer). The trade-off is power versus consistency; that is, the test without a trend is more likely to reject the null if the null is false. For a more detailed discussion, see DeJong and Whiteman (1991).

TABLE 3

Cointegration Tests: Johansen Trace Test Statistics[a]

Number of Cointegrating Vectors			
0	≤ 1	≤ 2	≤ 3
73.61	31.91	9.31	0.63

Distribution of Statistic (4 variables)			
50%	90%	95%	99%
33.67	43.96	47.18	53.79

a. Number of observations = 108.
SOURCE: Author's calculations (using modified Rasche RATS program) and Johansen and Juselius (1989, table D.1).

TABLE 4

Wald Tests[a]

Component level	Wald Test Statistic	Significance
Industrial production	–567	> 99.9
Reserves	–580	> 99.9
Deposits	–34,411	> 99.9
Loans	–28,970	> 99.9

a. Tests to determine whether components of cointegrating vector equal zero.
SOURCE: Author's calculations.

number of cointegrating vectors is less than or equal to one, two, or three. This indicates the existence of only one cointegrating vector or, in the terminology of Stock and Watson (1988), one common stochastic trend.

In examining table 3, it is useful to keep in mind the hypothesis generated earlier. First, from the model, if innovation in the banking sector has an effect on aggregate output, no common trend is anticipated. (I take as a given that some macroeconomic shocks over the period — the drought in the 1930s, World War II, and the oil embargo of the 1970s — were not driven by the banking sector.) Only in extreme cases, such as when banking has no separate efficiency gains of its own, will a common trend emerge. Second, I seek confirmation of Mitchell's observation that combinations of banking variables track the cycle more closely than any single series. That is precisely what the multivariate cointegration tests reveal: which linear combinations are stationary.

In this four-variable system, finding one common trend does not immediately show cointegration between the banking and industrial sectors. Perhaps the trend relates only the three banking variables. Formally, this would mean the industrial production term would be zero; the stationary combination would be a linear combination of the three banking variables. Table 4 uses a Wald test for this possibility, checking whether the loans, deposits, or reserves term is zero.[3] None of the four components is zero.

Finding cointegration between the banking sector and the industrial sector has mixed implications. On the one hand, the simple model of section I predicted no cointegration. Within the context of the model, this means that the long-run pace of bank efficiency and technological change is not distinct from that of the rest of the economy; one stochastic trend drives them both. The model still allows banks to affect the economy by transferring and propagating shocks originating in the industrial sector. In a broader model, banks could propagate other shocks not modeled here, such as monetary disturbances.

On the other hand, the result confirms the intuition of Mitchell, that *combinations* of banking variables track the rest of the economy well. Mitchell points out that one of the best barometers of the business cycle is the deposit-to-loan ratio. The common trend between financial variables and industrial production reinforces a more elaborate version of this intuition. The results uncover a more complicated long-run relation between industrial production and a linear combination of loans, deposits, and reserves.

VECM Results

The cointegration tests do not estimate the relationships between the variables and hence provide only qualitative information about series comovements. Two other approaches offer a more quantitative picture. One approach estimates the cointegrating vector itself. The other uses vector autoregression techniques to look at the variables' comovements. Since the variables exhibit cointegration, the regular vector autoregression should be replaced by Engle and Granger's (1987) vector error-correcting model (VECM).

The estimates of the cointegrating vector and the VECM are natural complements to the cen-

3 For a good description of the general Wald test, see Judge et al. (1985). For the specific use here, see Johansen and Juselius (1989).

TABLE 5

Vector Error-Correcting Representation

$$
\begin{pmatrix} \Delta Loan_t \\ \Delta Dep_t \\ \Delta Resv_t \\ \Delta IP_t \end{pmatrix} = \begin{bmatrix} 0.402 & -0.205 & 0.097 & 0.071 \\ -0.208 & -0.102 & 0.124 & -0.055 \\ 0.052 & -0.189 & 0.057 & -0.227 \\ -0.198 & 0.602 & 0.115 & -0.008 \end{bmatrix} \begin{pmatrix} \Delta Loan_{t-1} \\ \Delta Dep_{t-1} \\ \Delta Resv_{t-1} \\ \Delta IP_{t-1} \end{pmatrix} + \begin{bmatrix} -0.076 & 0.163 & 0.034 & 0.151 \\ -0.389 & -0.064 & 0.086 & 0.247 \\ -0.365 & 0.332 & -0.001 & 0.100 \\ 0.261 & 0.229 & -0.351 & 0.091 \end{bmatrix} \begin{pmatrix} \Delta Loan_{t-2} \\ \Delta Dep_{t-2} \\ \Delta Resv_{t-2} \\ \Delta IP_{t-2} \end{pmatrix}
$$

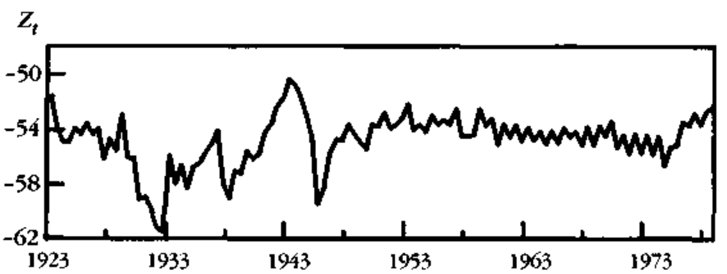
$$
+ \begin{bmatrix} -0.157 & -0.164 & 0.151 & 0.026 \\ -0.080 & -0.099 & 0.018 & 0.199 \\ -0.176 & -0.030 & 0.101 & -0.004 \\ -0.119 & -0.311 & 0.173 & -0.328 \end{bmatrix} \begin{pmatrix} \Delta Loan_{t-3} \\ \Delta Dep_{t-3} \\ \Delta Resv_{t-3} \\ \Delta IP_{t-3} \end{pmatrix} + \begin{bmatrix} 0.072 & 0.140 & 0.008 & -0.197 \\ 0.051 & 0.099 & 0.006 & -0.140 \\ -0.053 & -0.103 & -0.006 & 0.145 \\ -0.039 & -0.076 & -0.005 & 0.108 \end{bmatrix} \begin{pmatrix} Loan_{t-4} \\ Dep_{t-4} \\ Resv_{t-4} \\ IP_{t-4} \end{pmatrix}
$$

$$
+ \begin{pmatrix} 0.792 \\ 0.560 \\ -0.597 \\ -0.404 \end{pmatrix} + \begin{pmatrix} 0.050 \\ 0.066 \\ 0.050 \\ -0.034 \end{pmatrix} DSEAS
$$

SOURCE: Author's calculations.

FIGURE 8

Stationary Vector from Data



SOURCE: Author's calculations based on data from the Board of Governors of the Federal Reserve System and from U.S. Department of Labor, Bureau of Labor Statistics.

tral test of the model. Although the test rejects the hypothesized form of long-run interaction, it yields an estimate of both long-run and short-run interactions. This can offer insight into why the model failed, guide future hypotheses, and further explore the relation between the banking sector and business cycles.

The estimate of the cointegrating vector is (–4.865, –9.498, –0.569, 13.394). Normalizing the vector to give the industrial production (IP) component a value of one yields a stationary series of $Z_t = IP_t - 0.36 LOAN_t - 0.71 DEP_t - 0.04 RESV_t$. Notice how every banking component is negative and has an absolute value smaller than one. The scale undoubtedly reflects the units used, but the sign suggests that the stationary variable, or stable long-run relationship, is between IP and a weighted average of the banking variables. This relation was estimated in logs, so in levels it indicates a relation between IP divided by all three banking variables.

Figure 8 plots this series and represents a modern distillation of Mitchell's ideas, confirming that a combination of banking variables tracks the rest of the economy. Since it is not a straight line, it also shows the imperfections in that tracking.

More detail emerges from the VECM representation. The Granger representation theorem (Engle and Granger [1987]) states that cointegrated series have a VECM representation. Intuitively, this treats the observed series as a combination of two parts. The first, the stationary linear combination of variables, defines the "long-run equilibrium" relation of the variables. The second describes the reaction to shocks and superimposes the adjustment back toward the long-run relation (error correction).

The estimate for my system of industrial production, loans, deposits, and reserves uses four lags, a constant and a seasonal dummy, and thus takes the general form

$$
(16) \quad X_t = \Gamma_1 \Delta X_{t-1} + \Gamma_2 \Delta X_{t-2} + \Gamma_3 \Delta X_{t-3} + \Pi X_{t-4} + \mu_t + \gamma \, DSEAS.
$$

The difference between equation (16) and a vector autoregression in differenced form is the undifferenced term ΠX_{t-4}. Table 5 shows the actual estimates for the system.

In interpreting table 5, keep in mind that since the data are in logs, the coefficients represent elasticities. For example, a 1 percent increase in loan growth last period ($\Delta Loan_{t-1}$) is associated with a four-tenths of 1 percent increase in industrial production this period. This estimation is not meant to imply causality. Some of the patterns may result from some third influence, such as monetary or fiscal policy. Or, banks may increase loans when they forecast an economic recovery; loans would lead industrial production, but not cause it. The shift in loans itself may not be an exogenous decision of banks, but rather may be a response to another stimulus, such as a shift in deposits. Thus, the coefficient would not represent the effect of, say, a regulatory change that increased the number of loans.

Two features in table 5 stand out. First, the interactions among the four variables are quite complicated, varying in size and sign across lag lengths. Second, the impact of financial variables on industrial production (seen as the last row of each matrix) is generally large compared with other effects. Though banks may not originate business cycles, they do serve to transmit and propagate them.

Delving more deeply into the error-correcting form of table 5 can unlock more information. First, we must understand how such a model works.

The simplest type of error-correcting mechanism looks like

$$(17)\quad \Delta x_t = -\gamma z_{t-1} + u_t .$$

The change in x_t depends on the errors z_{t-1}, or deviations from equilibrium; x_t adjusts back to the equilibrium levels. But we have a model of what the equilibrium is (what cointegration tells us), so the definition of the errors is then just $z_{t-1} = \alpha' x_{t-1}$, where α is the cointegrating vector.

The system can adjust toward equilibrium in a more complex fashion than described by equation (17). Building in this adjustment filter, the general VECM takes the form $A(L)\,\Delta x_t = -\gamma z_{t-1} + u_t$. Table 5 has this form.

The error-correcting form clearly highlights the identification problem that prevents deriving structural conclusions from the reduced-form model. Any invertible matrix R can be used to rewrite $\gamma\alpha'$ as $(\gamma R)(R^{-1}\alpha')$. To identify either the cointegrating vector, the structural long-run relationship, or the error-correcting mechanism, R must be somehow restricted, perhaps by bringing in economic theory.

The theoretical model of section I does not place enough restrictions on R to identify the system. With only one cointegrating vector, however, information can be obtained from the sign pattern of the error-correction term. The 4x4 matrix on x_{t-4} in table 5 decomposes into a 4x1 γ vector and a 1x4 cointegrating vector. In this case, the R matrix must be scalar. This still prevents identification, but it allows some inferences about the sign pattern of γ.

If we assume $R > 0$, then $-\gamma$ has sign pattern (-,-,+,+), where the variable order is loans, deposits, reserves, and industrial production. If $R < 0$, $-\gamma$ takes the opposite sign. This sign pattern hardly reveals a detailed structural model, but it does uncover some broad features of such a model. Some series move the system toward equilibrium and serve to dampen fluctuations, while others move the system away from equilibrium and intensify fluctuations. The difference hinges on which sign is chosen for R. Imposing a restriction chooses between the cases, but this is unnecessary. Industrial production and reserves work in the same direction, opposite to loans and deposits.

Some conclusions also follow from looking at the filter, or the adjustment process defined by the coefficients on differenced lags in table 5. The adjustment process is complex; a shock to one variable today will affect not only the variable's future values, but future values of the other variables, which in turn will impinge on each other.

To make some sense of the complexity, recall my basic purpose of exploring the effect of banking shocks on aggregate output. Looking at the error-correcting component reveals the effect of temporary shocks. It then makes sense to concentrate on the industrial production components. The largest single effect comes from the first lag of deposits. The pattern of adjustments shows that the effect of loans on industrial production changes sign and exhibits a humped shape.

III. Conclusion

This simple study establishes some interesting points. It shows that common trends should not be expected between banking and industrial sectors, and emphasizes the rich dynamics inherent in that interaction. A long-run equilibrium relationship exists between banking variables and industrial production. This implies that banking is not driven by a separate long-run technology shock independent from the industrial sector. Short-run shifts do have an impact, which varies by sign, size, and time pattern across banking variables. Though invalidating the particular theory of section I, the results confirm and update Mitchell's insight on the close connection between banks and business cycles.

Future research could unveil some further possibilities. It would be useful to have a model that could discuss the monetary effects of financial innovations and delineate the separate roles of money and credit. Such a distinction is suggested by the finding that reserves and deposits, monetary variables, do not share a common trend with loans, a credit variable. Finally, a cross-country comparison would provide needed perspective, especially with a country like Japan, whose banking sector is more dominant in credit markets and more closely tied to the industrial sector.

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