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Bank Portfolio Composition and Macroeconomic Activity

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This paper examines the effects of bank portfolio composition by computing variance decompositions from a vector autoregressive model that comprises a portfolio composition variable (the ratio of commercial and industrial loans to total loans and security holdings), output, the price level, an interest rate, the money supply, and a supply shock variable. Using data from 1974:7–1989:12 and 1979:10–1989:12, bank portfolio composition is found to have significant effects on macro variables. Whether these effects should be interpreted as the result of monetary policy actions or the response to changes in loan demand is discussed.

I. Introduction

The role of bank portfolio composition in the monetary transmission process has been debated for many years. In the conventional view, bank portfolio composition does not matter in the transmission of the effects of monetary policy to the macroeconomy. In this view, an injection of reserves into the financial system leads to an increase in the money supply, a decrease in interest rates, and an increase in interest-sensitive spending. The effects will be the same whether the money created is generated by expansion of bank loans or by bank purchases of securities. As long as excess reserve holdings and borrowed reserves are insensitive to the mix of loans and securities in bank portfolios, the quantity of money created will be the same regardless of whether banks expand loans or buy securities following a reserve injection. A related aspect of the conventional view is that, for a given quantity of money, a shift from securities to loans by banks (due perhaps to a change in the perceived riskiness of loans) has no effect on spending.

This view has been challenged from several different perspectives. Silber (1969a) offers two reasons why bank portfolio composition matters. One focuses upon the magnitude and speed of response of different types of spending to changes in interest rates on loans and securities. Silber argues that, following a reserve injection, changes in loan rates due to an expansion of loans will have a larger and

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faster impact on spending than will changes in security yields due to a purchase of securities by banks. The basis for this argument is the contention that inventory investment is very responsive to changes in bank loan rates whereas other types of investment spending are less responsive to changes in security yields. A second rationale is that the velocity of money created by loans is greater than for money created by security purchases. The argument seems to be that deposits created by security purchases by banks will, at least initially, be held idle whereas deposits created by new loans will be spent immediately. These arguments suggest that, at least in the short-run, bank portfolio composition does matter.

More recent challenges to the traditional view that bank portfolio composition does not matter are found in the work of Bernanke (1983, 1988), Blinder and Stiglitz (1983), and Bernanke and Blinder (1988). In this literature, the basis for the view that bank portfolio composition matters rests upon the role of banks in the financial intermediation process. It is argued that banks service many small borrowers—both business and consumer—for whom borrowing in the open market would be, in the words of Bernanke (1988), "prohibitively expensive." The implication is that bank loans to this type of borrower finance expenditures that would not be financed in any other fashion. Thus, when banks curtail lending (perhaps due to monetary policy actions that drain reserves from the system or perhaps due to a desire by banks to rearrange their portfolios because of a change in the perceived risk of holding alternative assets), the spending plans of economic agents who have limited access to alternative forms of finance (like the issuance of commercial paper) are changed. For the system as a whole, the level of intermediary services is reduced, and, as a consequence, output is reduced. Gertler (1988) provides a comprehensive survey of how aspects of financial structure like bank portfolio composition matter for the macroeconomy.

An investigation of the macroeconomic effects of bank portfolio composition is thus suggested by several different theoretical arguments. The aim of this paper is to analyze empirically the effects of bank portfolio composition within the context of a small macroeconomic model. The empirical framework is a vector autoregressive (VAR) model that comprises output, the price level, a market interest rate, the money supply, a bank portfolio composition variable, and a supply shock variable. Monthly data for the period 1973–1989 are used to specify and estimate the model. The impact of bank portfolio composition is evaluated through computation of variance decompositions for which standard errors are calculated through Monte Carlo simulations. The effects of the other model variables on bank portfolio composition are evaluated in a similar fashion.

The VAR modeling approach is chosen because it is well suited to an examination of the channels through which bank portfolio composition influences macroeconomic activity because few restrictions are placed on the way in which the system variables interact. Because there is little consensus on the channels through which bank portfolio composition operates and on other aspects of structural models, the reduced-form VAR approach, rather than a structural model approach, is used. If a channel of influence is omitted from a structural model, the effects of bank portfolio composition may be misestimated. A desire to avoid this problem led to the use of the VAR procedure because the VAR model does not limit the potential interactions among the model variables. In the specification and estimation of the model, all variables are treated as jointly determined; no a priori assumptions are made about the exogeneity of any of the system variables. As is commonly known, it is difficult to distinguish sharply among structural hypotheses because the VAR approach is a reduced-form technique.[1] However, because the main purpose is to obtain insight into the effects of bank portfolio composition on output, the price level, and the interest rate, the VAR technique seems appropriate for this study.

Empirical evidence on the impact of bank portfolio composition on the macroeconomy is mixed. The empirical studies differ in a number of ways to include differences in sample periods, model specification, and measurement of bank portfolio composition. Bank portfolio composition is typically measured as the ratio of one component of bank assets (loans, for example) to total bank assets or by the level (or rate of change) in a component of bank assets.

Among the studies that used a ratio measure of bank portfolio composition, Silber (1969b) and Sutherland (1977) found significant effects of bank portfolio composition on the income velocity of M1. Lown (1990) found Granger causality from bank portfolio composition to real investment and real GNP. Kashyap, Stein, and Wilcox (1991) found that the ratio of bank loans to bank loans plus commercial paper had significant effects on several types of investment spending and that this variable was useful as a leading indicator of several macro variables. Batavia and Lash (1982) examined the effects of bank portfolio composition within a three equation model, but found their bank portfolio composition measure affected GNP at only the 10% level. However, Campbell (1978) estimated the effect of bank portfolio composition within a St. Louis-type distributed lag regression and found essentially no effect of bank portfolio composition on nominal GNP.

Among the studies using the level of a component of bank assets, Lown (1988) found evidence of Granger causality from bank loans to both nominal and real GNP. Bernanke (1986) and King (1986) both employed VARs in their analysis. In the case of Bernanke, variance decompositions based upon the Choleski decomposition indicated little effect of loans on the macroeconomy, whereas variance decompositions based upon Bernanke's structural VAR approach indicated that shocks to loans were about as important as those to money. King's variance decomposition results, derived using the Choleski decomposition and computed for both quarterly and monthly data, indicated little effect of bank portfolio composition on the economy, especially when interest rates were added to the model.

The current study differs from these earlier studies in several ways. First, a consistently defined series for bank portfolio composition is employed. In December 1972, the loan series used here was revised by the Federal Reserve to include data by a broader range of financial institutions. Only data after this revision are employed in this study. Many of the studies cited in the literature review gave no indication of how the consistency problem was handled. It is unclear whether the old series is merely merged with the new or whether some attempt is made to generate a consistent series. The importance of using a consistently defined series is suggested by the fact that the optimal lag in an autoregression of the bank portfolio composition variable (determined using Akaike's final prediction error criterion) is different when data for the old series

[1] Cooley and LeRoy (1985) have discussed other limitations of VARs.

for 1960:2–1972:11 are used and when data for the consistently defined series for the sample employed in this paper are used. A similar result is found when an attempt to create a consistent series over a longer sample is made by splicing the old series to the new by multiplying the old series by the ratio of the new to old series for the one observation (December 1972) in which the series overlap. These results suggest the importance of evaluating the effects of bank portfolio composition using the consistent series that begins in December 1972.

Second, like Batavia and Lash (1982), Bernanke (1986), and King (1986), the analysis is performed within a multiequation model. However, the effects of bank portfolio composition on prices and interest rates, as well as the output, are examined. This study thus provides a more comprehensive view of the effects of bank portfolio composition on macroeconomic activity than do the earlier studies. Third, the robustness of the results to inclusion of data prior to the October, 1979 change in operating procedures by the Federal Reserve is checked by estimating the model over the period after this policy change.

Section II discusses the data and the specification of the model and while the empirical results are presented and analyzed in Section III. A brief summary and conclusion is presented in Section IV.

II. Model Specification

As noted earlier, the macroeconomic effects of bank portfolio composition are evaluated within the context of a six-variable vector autoregressive (VAR) model. The model is specified and estimated using monthly data for the period 1973:1–1989:12. The period 1973:1–1974:6 is used as presample data, and the model is estimated over 1974:7–1989:12 and over 1979:10–1989:12. Furthermore, a dummy variable for the credit controls imposed during the Carter administration is included in each equation of the system. This variable takes on values of 1 from March to July 1980 and 0 in all other periods. No data prior to 1973:1 are used because the series for the bank portfolio variables underwent a revision in December 1972. The availability of a consistent series beginning in 1973 dictated the use of monthly data in order to have a sufficient sample size. A desire to reduce problems associated with temporal aggregation [see Christiano and Eichenbaum (1987)] also suggested the use of monthly data.

The model variables include: (1) a supply shock variable (SS) measured as the difference between the rate of change in the producer price index for crude oil and the rate of change in the consumer price index, (2) industrial production (IP), (3) the consumer price index, all items, urban consumers (CPI), (4) the M2 definition of money, (5) a short-term interest rate, the commercial paper rate (RCP), and (6) a bank portfolio composition variable, the ratio of commercial and industrial loans made by all commercial banks to the sum of total commercial bank loans and security holdings (PC). Ideally a fiscal policy variable like government purchases of goods and services or a marginal tax rate variable would be included in the model; however, the unavailability of monthly data for such series precluded the inclusion of these variables. All data are from Citibase and are seasonally adjusted with the exception of the interest rate.

Although many measures of bank portfolio composition have been employed in the empirical studies cited earlier, the basic measure of bank portfolio composition used in this paper is the ratio of commercial and industrial loans to the sum of total loans and security holdings of banks. The decision to focus upon commercial and industrial loans by banks is based upon Bernanke's argument that portfolio composition matters because bank loans to small borrowers finance expenditures that would not be financed in any other fashion. Although some recipients of these loans have access to other funding like the commercial paper market, this category of loans substantially meets the theoretical criterion of Bernanke. A broader measure of portfolio composition—the ratio of commercial and industrial loans plus loans to individuals plus mortgage loans to total loans and security holdings—is also considered in order to check the robustness of the results to the preferred portfolio measure. Neither the level of commercial and industrial loans nor the level of the more comprehensive loan measure are used because of the correlation of these variables with money. The nature of the money supply process suggests a close correlation of loans and the money supply. To reduce problems of this nature, the ratio form of the portfolio measure is used.

The supply shock variable is included in light of a great deal of evidence that a variable like the relative price of oil is an important determinant of macroeconomic behavior [see, for example, Rasche and Tatom (1981) and Hamilton (1983)]. The choice of the M2 definition of money is based upon the perception that the velocity of M2 is relatively less affected by the financial innovation and deregulation of the 1980s than is the velocity of M1 [see, for example, Hetzel and Mehra (1989)]. However, the sensitivity of the results to the use of M1 or the monetary base (adjusted for reserve requirement changes) in place of M2 is checked. Because of concerns about the appropriateness of the measurement of housing costs prior to 1983 in the CPI, all items, the sensitivity of the results to the use of this variable is checked by substituting the CPI for all items excluding shelter.

Because most of the VAR studies summarized in Todd (1990) used a short-term interest rate, a short-term interest rate is employed in the model. The focus of attention is the 6 month commercial paper rate; this is based upon the argument of Friedman and Kuttner (1989) that the commercial paper rate more directly corresponds to the cost of borrowing for interest-sensitive expenditure than does the treasury bill rate. Again, though, the sensitivity of the results to the use of the commercial paper rate is checked by considering two alternative short-term rates—the treasury bill rate and the federal funds rate—and a long-term rate, the AAA corporate bond rate. The treasury bill rate is examined because many of the VAR studies reviewed in Todd (1990) employ this variable. The federal funds rate is considered based upon the arguments of Bernanke and Blinder (1990) that this rate is a good measure of monetary policy. The long-term rate is considered because it might be argued that some components of investment spending are more responsive to the long-term rate than to a short-term rate.

Prior to specification and estimation of the VAR, augmented Dickey–Fuller tests were employed to check for first-order unit roots. The results of these tests are reported in Table 1A. These tests suggested that first differences of the logs of IP, CPI, M2, and PC and the first difference of the level of RCP should be used to specify and estimate the models. Additionally, because unit roots were indicated for the log levels of both CPI and the producer price index for crude oil and for the log level of the producer price index for crude oil minus the log level of the CPI, the appropriate supply shock measure appears to be the log difference of the producer price index for crude oil minus the log difference of the CPI.

Table 1. Unit Root and Cointegration Tests

Test	Variable	Estimated Test Statistic	
A. Unit root[a]	LIP	−3.02	
	LCPI	−1.07	
	LPPIC	−1.50	
	LSS	−1.59	
	LM2	−0.71	
	RCP	−1.89	
	LCI	−1.64	
		Engle and Yoo[b]	Hansen[c]
B. Cointegration	LIP	−2.50	−2.21
	LCPI	−2.07	−1.18
	LSS	−2.44	−2.75
	LM2	−2.02	−0.11
	RCP	−2.91	2.76
	LCI	−2.65	−2.25

[a]LIP, LCPI, LPPIC, LM2, and LCI are the log levels of IP, CPI, the producer price index for crude oil, M2, and CI, respectively. LSS is the difference of the log of the producer price index for crude oil and the log of the CPI. The critical value of the test statistic at the 5% level is ≡ −3.46 and is taken from Table 1 of Guilkey and Schmidt (1989). Fourteen lags are employed in the tests. The lag length is determined based upon the criterion proposed by Schwert (1987).

[b]Fourteen lags are employed in the tests. The critical value at the 5% level is −4.36 and is taken from Table 3 of Engle and Yoo (1987).

[c]Fourteen lags are employed in the tests. The critical value at the 5% level is −3.46 and is taken from Table 1 of Guilkey and Schmidt (1989). This is the value for 175 observations; the second-stage Hansen test regressions used 171 observations.

Based upon the arguments of Engle and Granger (1987), cointegration tests were also performed, and the results are reported in Table 1B. Cointegration tests of the sort suggested by Engle and Yoo (1987) were performed. However, because Hansen (1990) pointed out that the power of this test, as well as the test proposed by Johansen (1988), falls substantially as the size of the system increases, Hansen's two-stage test was also employed. The power of Hansen's test is unaffected by the size of the system. Neither the Engle–Yoo nor the Hansen tests yielded any evidence of cointegration. Because no evidence of cointegration was found, the system was estimated with the differenced variables.[2] These variables are defined as follows: DLIP, DLCPI, DLM2, and DLPC are the first differences of the logs of IP, CPI, M2, and PC, respectively, and DRCP is the first difference of RCP. SS denotes the first difference of the log of the producer price index for crude oil minus DLCPI.

The appropriate lag length for the VAR model was determined from a sequence of likelihood ratio tests. A maximum lag of 18 was considered and the likelihood ratio tests were computed in a manner consistent with Anderson (1971) with the small sample correction suggested by Sims. The testing began with a comparison of an 18 lag model with a 17 lag model. If the null hypothesis that the 18th lag were zero could not be rejected, the 17 lag model was tested against a 16 lag model. This

[2] The results reported are for a model in which each equation includes a constant and lagged values of each variable in the system. The results are robust to the inclusion of a deterministic trend in each equation. When a trend was added to each equation, the variance decomposition results were all within 1 standard deviation of those reported in Tables 1 and 2.

continued until the null hypothesis was rejected. The optimal lag was found to be 16. Q statistics indicated the absence of any serial correlation in the residuals of the 16 lag model.

III. Empirical Results

As noted in Section I, the effects of bank portfolio composition are evaluated through the computation of variance decompositions (VDCs). VDCs indicate the proportion of the forecast error variance of a variable explained by shocks to itself and the other variables in the system. For example, the VDC for DLIP indicates the percentage of the forecast error variance of DLIP explained by shocks to DLPC and the other variables in the system. If DLPC is an important determinant of movements in output, the price level, and the interest rate, one would expect DLPC to explain a significant fraction of the forecast error variation of these variables. Because Runkle (1987) noted that reporting VDCs without associated standard errors is similar to reporting regression coefficients without t statistics, a Monte Carlo integration procedure like that described in Doan (1990) is used to generate standard errors for the VDCs. One-thousand draws are employed in the Monte Carlo procedure. The estimates of the proportion of forecast error variance explained by DLPC are judged to be "significant" if the estimate is at least twice the standard error.

Because the equations of the VAR contain only lagged values of the system variables, any contemporaneous relations among the variables are reflected in the correlation of residuals across equations. There are two common ways to deal with this contemporaneous correlation in the computation of VDCs.[3] One is to order the variables in a particular fashion and then use the Choleski decomposition to orthogonalize the variance–covariance matrix. In this approach, when a variable higher in the order changes, variables lower in the order are assumed to change. The extent of the change depends upon the covariance of the variables higher in the order with those lower in the order. An alternative approach is to use the structural VAR model approach of Bernanke (1986). In this approach the researcher employs the residuals from the VAR model in the estimation of a structural model. In this way the contemporaneous correlation across the VAR model residuals is purged, and the residuals of the structural model are interpreted as fundamental shocks. To check the robustness of the effects of portfolio composition, both approaches are employed in this paper.

Because lagged values of all variables in the system are included in each equation in the system, it is assumed that the residuals from the DLPC equation are purged of the effects of past economic activity on bank portfolio composition. Furthermore, for the Choleski decomposition DLPC is ordered last. Ordering DLPC last is consistent with the set of structural models in which the variables other than DLPC have both direct and indirect contemporaneous effects on DLPC. This purges the shocks to DLPC of any effects of current economic activity on bank portfolio composition. It is thus assumed that these shocks to DLPC

[3] Blanchard and Quah (1989) recently suggested a third alternative that involves imposing long-run restrictions to identify fundamental shocks.

represent variation in bank portfolio composition that is independent of current and past economic activity. The effects of DLPC on the other variables do not depend upon the order in which these variables precede DLPC. That is, when DLPC is ordered last, the effect of DLPC on, for example, DLIP is the same whether DLIP is ordered first or next to last. This procedure does preclude any *contemporaneous* effects of DLPC on the other variables; in this ordering, a shock to DLPC today first affects the other variables in the next month.

The VDCs for the Choleski decomposition for the period 1974:7–1989:12 are presented in Table 2. The ordering that underlies the results in this table is SS,

Table 2. Variance Decompositions for the 1974:7–1989:12 Sample[a]

		1 DLM2	2 DLPC	3 DLPCA	4 DLPC	5 DLPC	6 DLPC	7 DLPC	8 DLPC	9 DLPC	10 DLPC
DLIP	6	3.0 (2.3)	9.1 (3.7)*	6.6	9.0	9.8	7.8	9.8	7.3	11.1	9.5
	12	6.2 (3.0)*	11.3 (3.9)*	7.0a	10.1	11.1	12.8	13.4	10.0	12.1	12.8
	24	8.5 (3.3)*	12.0 (3.6)*	7.8a	10.5	11.1	12.7	13.1	9.8	12.7	13.0
	36	9.1 (3.3)*	12.1 (3.5)*	8.3a	11.1	10.3	12.3	13.0	9.8	12.9	13.0
	48	9.4 (3.6)*	11.9 (3.5)*	8.3a	11.0	10.3	12.1	12.8	9.7	12.8	12.8
DLCPI	6	4.9 (2.9)	1.8 (1.9)	1.1	1.1	1.0	2.6	3.2	1.4	3.2	2.0
	12	9.5 (4.4)*	3.4 (2.2)	2.1	3.2	1.6	2.7	4.5	2.2	5.2	3.7
	24	12.8 (5.9)*	4.8 (3.7)	3.7	7.6	1.4	3.0	4.3	4.7	5.9	4.7
	36	13.6 (6.8)*	4.7 (4.3)	3.4	8.4	2.2	3.0	3.8	5.9	5.8	4.8
	48	13.4 (7.1)	4.5 (4.5)	3.1	8.5	3.4	2.9	3.6	6.5	5.6	4.6
DRCP	6	6.2 (2.8)*	2.6 (2.3)	1.1	2.3	3.0	3.9	5.5a	2.3	3.9	2.6
	12	7.3 (3.0)*	4.3 (2.3)	5.2	2.9	5.6	5.0	7.3a	2.8	5.7	4.7
	24	12.5 (3.6)*	7.3 (2.8)*	8.2	6.8	6.6	6.7	7.7	5.6	8.6	8.0
	36	13.3 (3.9)*	8.4 (3.1)*	9.4	8.1	7.9	7.4	8.3	5.8	10.0	9.0
	48	13.5 (4.1)*	8.4 (3.2)*	9.6	8.2	7.8	7.4	8.4	6.0	10.1	9.0

[a]The numbers in columns 1–10 are point estimates of the variance decompositions. The numbers in parentheses are estimates of standard errors. An asterisk indicates that the point estimate is at least twice the standard error. The results in columns 1 and 2 are for DLM2 and DLPC, respectively, for the basic model. The results in column 3 are for a model in which the expanded portfolio measure (DLPCA) replaces PC; in column 4 for a model in which M1 replaces M2; in column 5 for a model in which the monetary base replaces M2; in column 6 for a model in which the treasury bill rate replaces RCP; in column 7 for a model in which the federal funds rate replaces RCP; in column 8 for a model in which the AAA rate replaces RCP; in column 9 for a model in which the CPI excluding shelter replaces CPI; in column 10 for the Bernanke-type structural VAR. The suffix a indicates the number is within 2 standard deviations of that in column 2; all other entries in columns 3–10 are within 1 standard deviation.

DLIP, DLCPI, DRCP, DLM2, DLPC.[4] The estimated standard errors are shown in parentheses next to the point estimates of the VDCs. An asterisk indicates the point estimate is at least twice the standard error. VDCs at horizons of 6, 12, 24, 36, and 48 months are presented to convey a sense of the dynamics of the system.

The first two columns present the effects of DLM2 and DLPC, respectively, on DLIP, DLCPI, and DRCP. The effects of DLM2 are included for purposes of comparison with those of DLPC.[5] From column 2 we see that DLPC has significant effects on DLIP and DRCP (at longer horizons). The effects on DLCPI are insignificant. At the longer horizons, the effects on DLIP (12%) are stronger than for DRCP (8%). The effects on DLIP are of comparable magnitude to those of DLM2 on DLIP; in fact, the point estimates are somewhat higher for DLPC than for DLM2. The point estimates of DLM2 on DLCPI and DRCP are, however, higher than the point estimates of the effects of DLPCs on these variables. Based upon these results, it would appear that the effects of DLPC on DLIP are consequential. The effects on DLCPI and DRCP are less substantial, however. Furthermore, DLM2 shocks appear to be of consequence for all three of these variables.

It is important to determine how robust the results are. To check this, a number of modifications in the basic model were made. Columns 3–9 of Table 2 present the proportions of the variation in DLIP, DLCPI, and DRCP explained by the portfolio composition variable for various alternative models. The results in column 3 are for a model in which the first difference of the log of the ratio of commercial and industrial loans plus individual loans plus mortgage loans to total loans and securities replaces DLPC; those in column 4 are for a model in which the first difference of the log of M1 replaces DLM2; those in column 5 are for a model in which the first difference of the log of the monetary base replaces DLM2; those in column 6 are for a model in which the first difference of the treasury-bill rate replaces DRCP; those in column 7 are for a model in which the first difference of the federal fund rate replaces DRCP; those in column 8 are for a model in which the first difference of the AAA bond rate replaces DRCP; those in column 9 are for a model in which the first difference of the log of the CPI excluding shelter replaces DLCPI.

The effects of the expanded portfolio variable (column 3) are similar in nature

[4] Ordering DLPC last is the least favorable position for DLPC because credit for contemporaneous correlation between DLPC and the other variables is assigned to the other variables. Placing DLM2 next-to-last allows current shocks to money to affect portfolio composition, but also allows contemporaneous effects of SS, DLIP, DLCPI, and DRCP on money. The results for both DLPC and DLM2 in Tables 1 and 2 are robust to other orderings. Other orderings considered are (1) SS, DLIP, DLCPI, DRCP, DLPC, DLM2, (2) SS, DLM2, DLPC, DRCP, DLIP, DLCPI, and (3) SS, DLPC, DLM2, DRCP, DLIP, DLCPI. SS is always placed first because it is assumed that contemporaneous shocks to oil prices can be attributed more to developments in world oil markets than to shocks to the other variables in the system. Ordering 1 merely reverses the positions of DLM2 and DLPC in the orderings presented in the text. In orderings 2 and 3, the money and portfolio composition variables precede the interest rate that precedes the goods market variables, DLIP and DLCPI. In these orderings innovations in money and portfolio composition are allowed to contemporaneously alter the interest rate, which in turn alters the goods market variables.

[5] This seems useful because Bernanke (1986) and Fackler (1990) find that their credit measures are at least as important as money in explaining macroeconomic variables. Neither author, however, examines the type of bank portfolio composition measures used here.

to those for DLPC (column 2). All effects of the alternative measure are within 2 standard deviations of those for DLPC; indeed, most are within 1 standard deviation. The point estimates of the expanded measure are lower for DLIP and DLCPI but higher for DRCP than are the point estimates of DLPC. The point estimates of the effects of DLPC for the alternative models in columns 4–9 are all within 2 standard deviations of those in column 2 and are generally within 1 standard deviation. The results do not appear sensitive to the types of changes in the basic model made in generating columns 3–9.

A concern about the sample employed here is that it includes data before and after the October, 1979 change in the operating procedures of the Federal Reserve. It is desired to see if the 1974:7–1979:9 period differs from the 1979:10–1989:12 period. This is accomplished by estimating the basic model and the alternatives over the 1979:10–1989:12 period. A lag of 13 months generated white noise residuals over this period.

Table 3 presents the VDC results for 1979:10–1989:12. All columns are defined analogously to those in Table 2. Both DLM2 and DLPC have significant effects of comparable magnitude on DLIP, DLCPI, and DRCP. The point estimates of the

Table 3. Variance Decompositions for the 1979:10–1989:12 Sample[a]

		1	2	3	4	5	6	7	8	9	10
		DLM2	DLPC	DLPCA	DLPC	DLPC	DLPC	DLPC	DLPC	DLPC	DLPC
DLIP	6	5.3	7.4	7.6	8.7	6.7	6.6	9.1	8.8	8.6	12.2a
		(2.9)	(3.5)*								
	12	9.5	9.6	9.7	7.6	7.8	10.4	8.5	10.6	12.0	15.4a
		(3.5)*	(3.4)*								
	24	13.8	12.0	14.7	13.0	10.0	13.8	11.6	11.9	13.9	17.7a
		(4.2)*	(3.8)*								
	36	14.9	13.3	15.2	14.3	10.1	14.3	12.3	13.0	14.0	19.2a
		(4.5)*	(4.3)*								
	48	14.9	14.0	15.7	14.9	10.2	14.5	13.0	13.3	13.9	19.5a
		(4.9)*	(4.8)*								
DLCPI	6	6.7	4.8	1.3a	3.9	1.5	4.8	3.4	4.5	5.0	5.4
		(3.9)	(2.8)								
	12	8.8	7.3	2.4a	5.7	3.8a	6.8	8.0	6.5	7.5	7.8
		(4.5)	(3.0)*								
	24	11.4	10.1	9.1	9.2	5.7a	9.8	9.7	9.6	9.1	10.4
		(5.2)*	(3.7)*								
	36	11.5	9.9	9.5	8.8	5.6a	9.6	9.3	9.5	9.0	10.1
		(5.1)*	(3.8)*								
	48	11.6	10.4	9.8	9.1	5.5a	9.9	9.6	10.0	9.5	10.6
		(5.3)*	(4.3)*								
DRCP	6	4.2	6.1	1.3a	4.0	7.3	8.5	5.1	8.5	5.7	9.7a
		(2.9)	(3.5)								
	12	9.7	6.2	5.2	5.3	8.5	6.9	6.7	9.0	8.4	10.9a
		(4.1)*	(3.1)*								
	24	11.1	12.2	8.9	10.1	11.2	11.1	10.5	13.6	12.1	16.1
		(4.1)*	(4.1)*								
	36	12.3	12.7	9.1	11.3	11.3	11.8	10.2	13.6	12.1	16.2
		(4.4)*	(4.4)*								
	48	12.3	13.3	9.4	12.0	11.6	12.5	10.5	14.2	12.4	16.7
		(4.8)*	(4.9)*								

[a]See footnote to Table 2.

effects of the expanded portfolio measure are of a similar magnitude to those of DLPC. As before, the results for 1979:10–1989:12 do not appear very sensitive to changes in the basic model. The results in columns 3–9 are typically within 1 standard deviation of those in column 2; in all cases, they are within 2 standard deviations.

When the results in Table 3 are compared to those in Table 2, we see that the results for DLM2 (column 1) are quite comparable to those in Table 2, although the point estimates for DLIP are somewhat higher than in Table 2. The magnitude of the effects of DLPC on DLIP are quite similar to those in Table 2. The point estimates for the effects of DLPC on DLCPI (column 2) are greater than before, and are now significant. However, these point estimates are within 2 standard deviations of those in Table 2. The effects of DLPC on DRCP are again significant at the longer horizons (12 months on), and the point estimates are about 50% greater than in Table 2, although they are still within 2 standard deviations of those in Table 2. The effects of the expanded portfolio composition variables on DLIP (column 3) have almost doubled and are now of similar magnitude to those of DLPC. The point estimates for the expanded portfolio composition measure for DLCPI have at least doubled in most cases, and are again comparable in magnitude to those of DLPC. The basic conclusion that DLPC has important macroeconomic effects is the same for both sample periods, but there do appear to be some differences in the magnitude of the effects, especially for DLCPI.[6] In fact, the effects of the portfolio composition variables appear stronger in the 1979:10–1989:12 period than in the longer period.

Finally, it should be noted that there is significant feedback from the other variables in the model to DLPC in both samples. These results, the details of which are available on request, indicate significant feedback from DLIP, DRCP, and DLM2 for 1974:7–1989:12 and significant feedback from all variables for 1979:10–1989:12. This is not unexpected because bank portfolio choices are expected to respond to movements in variables like DLIP, DLCPI, and DRCP and, hence, indirectly, through their effects on these variables, to SS and DLM2.

As mentioned earlier, the robustness of the results is further checked by employing Bernanke's alternative method of orthogonalizing the residuals of the VAR. The structural model employed in the Bernanke procedure is just identified and is written as

$$ss_t = e_{1t}, \tag{1}$$

[6] The stability of the model was formally tested by a straightforward multivariate extension of the procedure suggested by Dufour (1980, 1982). In the multivariate extension of this test, the system was first estimated with 16 lags on each variable over the 1974:7–1989:12 period. Dummy variables for each observation in the 1974:7–1979:9 period were then added to *each* equation in the system, and this system was estimated over 1974:7–1989:12. The joint significance of the coefficients on all the dummy variables was tested by a likelihood ratio test. When the test was computed with the small-sample correction suggested by Sims (1980), the calculated χ^2 statistic was 204.2. The marginal significance level of this statistic is 0.99. Thus the hypothesis that the coefficients on the dummy variables are jointly equal to zero cannot be rejected, and no instability is indicated. However, when the test is computed without the small-sample correction, the calculated χ^2 is 1461.0 with a marginal significance of 0.00. This test indicates instability. The substantial divergence between the test corrected for small-sample bias and the uncorrected test reflects the large number of parameters in the equations with the dummies (160) relative to the total observation.

$$dlip_t = a_{21}ss_t + a_{25}dlm2_t + a_{26}dlpc_t + e_{2t}, \quad (2)$$

$$dlcpi_t = a_{31}ss_t + a_{32}dlip_t + e_{3t}, \quad (3)$$

$$drcp_t = a_{42}dlip_t + a_{43}dlcpi_t + a_{45}dlm2_t + e_{4t}, \quad (4)$$

$$dlm2_t = a_{51}ss_t + a_{52}dlip_t + a_{53}dlcpi_t + a_{54}drcp_t + e_{5t}, \quad (5)$$

$$dlpc_t = a_{62}dlip_t + a_{63}dlcpi_t + a_{64}drcp_t + e_{6t}, \quad (6)$$

where the lowercase letters indicate the residuals from the VAR (i.e., ss_t = the residual from the SS equation in the VAR, etc.). Because there are 6 variables in the system 21 parameters [$\{n(n-1)/2\}$], where n is the number of variables in the system] can be estimated. Six of these parameters are the fundamental shocks (the $e_{it}s$) and 15 structural parameters can be estimated. The method of moments procedure described in Bernanke (1986) is used to solve the model.[7]

It is assumed that contemporaneous shocks to the relative price of oil stem more from developments in the world oil market than from shocks to the other model variables. Hence, equation (1) allows no contemporaneous effects of the other model variables on the relative price of oil. Equation (2) is an aggregate demand equation in which aggregate demand depends positively upon money and bank portfolio composition. Following Kahn and Hampton (1990), who argue that an increase in the relative price of oil reduces consumption expenditures and hence aggregate demand, relative oil prices are included in equation (2). Their argument is that foreign oil producers receive much of the increased expenditure on energy following an increase in the relative price of oil, and, as a consequence, income is shifted from domestic consumers to the oil producers. This in turn reduces aggregate demand. Although *dlcpi* does not appear explicitly in equation (2), it does appear implicitly because it is employed in the construction of *ss*.[8] The aggregate supply curve is represented by equation (3), and it is expected that there is a positive, contemporaneous relation between *dlcpi* and *dlip*. Changes in the relative price of oil are allowed to shift the aggregate supply curve; an increase in the relative price of oil is expected to reduce aggregate supply. Equation (4) is a typical money demand function in which the demand for nominal balances depends negatively upon the interest rate and positively upon output and the price level. The equation is normalized on the interest rate. Although one would expect the demand for nominal balances to rise one for one with the price level over time, the coefficient on *dlcpi* is not constrained to equal 1 because the model is estimated using only the contemporaneous values of shocks to monthly data. Equation (5) can be viewed as a reaction function in which money depends upon macro variables like *dlip*, *dlcpi*, and *drcp* and upon the relative price of oil. Because it is a reaction function, it is difficult to determine a priori the expected signs on the variables in equation (5). Finally, movements in *dlip*, *dlcpi*, and *drcp* are allowed to

[7] The program to estimate the fundamental shocks and the parameters of the model was provided by James S. Fackler.

[8] This effect is partially offset, in the view of Kahn and Hampton, by an increase in domestic spending by domestic oil producers. The offset is only partial because part of the increased spending by domestic oil producers goes to imported goods.

affect *dlpc* [equation (6)]. As economic activity rises, banks are hypothesized to expand loans as a proportion of assets. As the commercial paper rate rises, borrowers in this market are hypothesized to turn to banks for loans as an alternative to the increased cost of borrowing in the commercial paper market. The expected signs of the coefficients on *dlip*, *dlcpi*, and *drcp* are thus positive.

As with the Choleski method, the Bernanke procedure is employed for both the 1974:7–1989:12 period and the 1979:10–1989:12 period. Because the main purpose of using the Bernanke procedure in this paper is to examine the robustness of the VDC results to an alternative method of orthogonalizing the residuals, the coefficient estimates are not presented. The coefficients are generally of the anticipated sign, but are, as is frequently the case in this procedure, often not significantly different from zero.[9] The VDC results for the Bernanke-type decomposition reported in the last columns of Tables 2 and 3 are quite similar to those for the Choleski decompositions. We see that the point estimates are somewhat higher for DLIP and DRCP for the Bernanke-type decomposition than for the Choleski decomposition in column 2. However, we observe that the effects are, in all cases, within 2 standard deviations of those for the Choleski decomposition in column 2 and are generally within 1 standard deviation.

The results indicate that bank portfolio composition explains significant portions of the variation in macro variables like output, the price level, and the interest rate. The proper interpretation of these results is difficult, however. One interpretation that flows from the discussion in the introduction of this paper is that bank portfolio composition matters because it is a channel through which monetary policy operates. Monetary policy affects the supply of loans, and it is this effect on loan supply that generates the macro effects. An alternative explanation is given by King and Plosser (1984). In their view, the significant effect of the bank portfolio composition variable may reflect future real shocks. In the King–Plosser model, information about real shocks precedes the occurrence of the shock. In response to, say, information about a positive future shock to output, firms' demands for loans rise as firms begin gearing up for increased future production. The King–Plosser model deals with the volume of loans, but their argument can be extended in a straightforward fashion to the type of portfolio composition variable used here. With a given volume of reserves in the financial system, the ratio of loans to total assets of banks will rise if banks respond to the increased loan demand by selling securities or by expanding managed liabilities. Thus, the ratio of loans to bank assets will rise prior to any movement in output, although the change in bank portfolio composition reflects the response of banks to an increase in loan demand, not the effects of monetary policy actions.

Distinguishing between these two interpretations is very difficult, but important. There are several studies that have some bearing on this issue, but they are best interpreted as suggestive, not definitive. First, as noted by Lacker (1990), new information is often reflected first in the interest rate, so that inclusion of the commercial paper rate effectively picks up the effects of information about future shocks.

[9] See Fackler (1990) for a discussion of why so little contemporaneous significance is typically found.

Second, the studies of Bernanke and Blinder (1990) and Kashyap, Stein, and Wilcox (1991) provide some evidence that monetary policy actions have systematic effects on bank portfolio composition. Bernanke and Blinder argue that the federal funds rate is the best proxy for monetary policy actions, and they find that contractionary monetary policy actions lead, for approximately 6 months, to a decrease in security holdings at banks. After this period, security holdings are rebuilt whereas loans begin to fall. After about 2 years, security holdings rebound to almost their initial level whereas loans are lower than they were initially. Contractionary monetary policy actions thus lead to decreases in loans as a percent of total assets of banks. This pattern of adjustment is attributed to the quasi-contractual nature of loans that prevents rapid adjustment of bank loans. Kashyap, Stein, and Wilcox find that the federal funds rate (again employed as a monetary policy proxy) Granger-causes banks loans, and the coefficients in the regression used in the Granger-causality test indicate that contractionary monetary policy actions reduce bank loans.

Furthermore, Kashyap, Stein, and Wilcox argue that if the effect of bank loans on output reflects movements in credit demand, one would expect to see a change in the volume of other sources of credit, like commercial paper, in the same direction as bank loans. However, if monetary policy is responsible for the change in bank loans, one would expect to see the volume of commercial paper move in the opposite direction as firms with the ability to issue commercial paper adjust the volume of commercial paper outstanding. For example, if the Federal Reserve engages in a contractionary policy that leads to a reduction in bank loans, one would expect to see an increase in the volume of outstanding commercial paper as firms are able substitute commercial paper for bank loans. Using data from a sample that includes the years examined in this paper, Kashyap, Stein, and Wilcox find that commercial paper issuance rises when bank loans fall following contractionary monetary policy actions.[10] They interpret this as indicating that the effects of bank loans on macro activity reflect movements in loan supply and not shifts in credit demand.

Because one might question the measure of monetary policy used in these studies and the adequacy with which factors other than monetary policy have been controlled, the results just cited should be regarded as suggestive. Distinguishing between the two interpretations, although challenging, is an important area for future research.

[10] Kashyap, Stein, and Wilcox reach their conclusions based on several tests. One is premised on the Romer and Romer (1989) dating of shifts to tight monetary policy. Kashyap, Stein, and Wilcox find that commercial paper grows above *trend* for a year after shifts to tighter policy, whereas for bank loans, growth relative to *trend* slows two quarters after a shift to tighter policy. They also find that the federal funds rate Granger-causes commercial paper issuance and bank loans, and the coefficients in the regressions used in the Granger-causality tests indicate that contractionary monetary policy actions stimulate issuance of commercial paper while reducing bank loans. They note the possibility that increases in commercial paper stem from substitutions away from other funding sources like bonds rather than away from bank loans. However, commercial paper and bond issuance appear to be positively correlated, and analysis based on the Romer–Romer dating indicates bond issuance increases slightly relative to trend following tight policy. No Granger causality is found from the federal funds rate to bond issuance, although the coefficients in this regression are positive.

IV. Conclusion

Recent developments in macroeconomics like those of Bernanke (1988) and others have revived interest in the question of whether bank portfolio composition matters for macroeconomic variables. This paper examines the macroeconomic effects of bank portfolio composition within the context of a vector autoregressive model that, in addition to a portfolio composition variable, includes output, the price level, an interest rate, the money supply, and a supply shock variable. The model is estimated using monthly data for 1974:7–1989:12. However, because this sample includes data before and after the October, 1979 change in operating procedures of the Federal Reserve, the model is also estimated for the period 1979:10–1989:12.

The primary portfolio composition variable examined is the ratio of commercial and industrial loans to total loans and security holdings of banks. The sensitivity of the results to a broader measure that adds personal and mortgage loans to commercial and industrial loans is examined. Variance decompositions are computed to analyze the effects of portfolio composition and the money supply on output, the price level, and the interest rate. Monte Carlo simulations are employed to estimate standard errors for the variance decompositions, and the standard errors are used to determine whether the variance decomposition results are significant.

The results for the basic model indicate that, for both periods, bank portfolio composition has significant effects on macroeconomic variables. The effects of portfolio composition on output are essentially equal in magnitude to those of money in both sample periods. The effects of portfolio composition on the price level and the interest rate are again essentially equal in magnitude to those of money in the period 1979:10–1989:12, but are weaker, especially for prices, in the period 1974:7–1989:12. There appears to be significant feedback from the other model variables to bank portfolio composition. The results are quite similar for both portfolio composition measures and are also quite robust for a variety of other modifications to the basic model. The results are also robust to the method of purging contemporaneous correlation from the residuals of the VAR. Although most of the results for this paper are derived using the Choleski decomposition, quite similar results were obtained when the structural approach of Bernanke was employed.

A determination of whether these effects are the result of monetary policy actions or stem from response to changes in loan demand that reflect future real shocks is very difficult and is an important topic for further study. Kashyap, Stein, and Wilcox (1991) provide evidence that is suggestive that the effects of bank portfolio composition on macroeconomic activity stem from disruptions to loan supply rather than shocks to credit demand. If this is the case, it is worthwhile to consider macro models in which the effects of monetary policy are transmitted through bank portfolio composition as well as through changes in monetary aggregates and interest rates. The significance of the bank portfolio variables indicates these variables may be useful as information variables in the formulation of monetary policy, although the extensive feedback from the other model variables to bank portfolio composition renders questionable the use of portfolio composition variables as intermediate targets.

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