Identifying the Macroeconomic Effect of Loan Supply Shocks

Joe Peek**

Eric S. Rosengren*

and

Geoffrey M.B. Tootell*

Abstract

The inability to clearly distinguish the effects of shocks to loan supply from those to loan demand has made it difficult to quantify the economic importance of the credit channel in the transmission mechanism of monetary policy. This study provides an innovative approach to identifying loan supply shocks. Three different results confirm that loan supply shocks have been successfully isolated from shifts in loan demand: Our measure is particularly important for explaining inventory movements, the component of GDP most dependent on bank lending; the effect is present even during periods with strong loan demand; and the effect remains even when the unpredictable part of the loan supply shock is isolated. This identification enables us to show that loan supply shocks have had economically important effects on the U.S. economy.

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*Research Department, T-8, Federal Reserve Bank of Boston, 600 Atlantic Avenue, Boston, MA 02106, (617) 973-3090, fax: (617) 973-2123, Eric.Rosengren@bos.frb.org and Geoffrey.Tootell@bos.frb.org

** Gatton College of Business and Economics, University of Kentucky, Lexington, KY 40506-0034, (859) 257-7342, fax: (859) 257-9688, Jpeek0@uky.edu

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Identifying the Macroeconomic Effect of Loan Supply Shocks

In an earlier study, Peek, Rosengren, and Tootell (1999) established that confidential bank supervisory information could be used to improve macroeconomic forecasts and that, in fact, the Federal Open Market Committee considered this information when setting monetary policy. While this evidence provided support for the hypothesis that the central bank should retain bank supervisory authority to facilitate the conduct of monetary policy, it did not address an important underlying question: Why does the information on the health of the banking system improve macroeconomic forecasts? One possible explanation is that confidential supervisory information might be serving as a leading indicator of future macroeconomic activity. Alternatively, the financial health of the banking system might causally affect macroeconomic activity if the banking sector plays a central role in the transmission mechanism of monetary policy. This study addresses which of these two explanations the data support by focusing not only on real GDP, but on specific components of GDP that differ in, among other things, their reliance on bank financing, and thus in their sensitivity to the health of the banking system. The results are consistent with the second explanation, indicating that loan supply shocks do have significant effects on the macroeconomy, both in the sectors and in the manner one would expect if a credit channel were operative.

Despite widespread debate, the role of the credit channel in the transmission of monetary policy has remained unresolved. Although on a conceptual level broad agreement exists on how this channel might operate, two basic sources of skepticism remain about its practical importance. Some have argued that monetary policy shocks might not affect bank lending as long as banks insulate their portfolios from these shocks, while others have argued that firms can access alternative credit sources if bank loan supply does tighten. Because doubts about the existence of an operative credit channel have focused primarily on this second issue, most empirical studies have examined whether shocks to the supply of bank loans affect the real economy. However, serious questions remain about the extent to which these empirical studies have successfully controlled for loan demand.

This study attempts to address this identification problem by more effectively controlling for changes in loan demand and by using a better measure of disturbances to loan supply. Unlike the previous literature, model-driven commercial forecasts of real economic activity are used to control for loan demand. Tests of the efficiency of commercial forecasts show that they contain all publicly available information about the state of aggregate demand (and supply). Furthermore, since a firm's demand for loans depends crucially on the demand for its products, the ability to account for aggregate demand is essential to controlling for loan demand. Since the models used by commercial forecasters are much richer than those used in previous macro research in this area, the approach more completely controls for changes in loan demand.

In addition, confidential bank supervisory information about bank health is used to measure loan supply shocks, avoiding two serious problems associated with earlier tests. Previous studies at the macro level correlate changes in measures of firm or bank activities with measures of shifts in monetary policy. As is well known, the identification of monetary policy shocks presents its own set of difficulties (Romer and Romer 1990; Hoover and Perez 1994; Leeper 1997; Bernanke and Mihov 1998). Perhaps even more problematic, whatever the method used to identify monetary policy shocks, these disturbances are, by their very nature, correlated with shifts in loan demand. Any decline in bank loans associated with a tightening of monetary policy could be caused either by a cutback in lending by banks or by a decline in loan demand brought on by the weaker economy working through the other channels of monetary policy. By using a direct measure of disturbances to loan supply, we avoid the need to identify shifts in monetary policy in order to test for the effects of loan supply shocks on the economy. Furthermore, the ensuing test avoids the identification problems associated with using a loan supply shock measure that is, by its very nature, correlated with changes in loan demand. Thus, any effect of this bank health variable on output represents a cleaner measure of loan supply effects on aggregate activity than is found in the previous literature.

These improvements in the method for controlling for shocks to loan demand and measuring disturbances to loan supply are incorporated into three sets of tests that provide compelling evidence that the effect on the real economy of shocks to banks' loan supply has been identified. Additional steps are required to identify loan supply and loan demand shocks because these forecasts fail to account completely for such disturbances. Although commercial forecasts of GDP and its major components control for demand shocks on average, in the short run, errors are made. These short-run errors could reflect errors in loan demand, in addition to loan supply, which the bank health variable is capturing. Thus, we begin by ensuring that the effect of the loan supply measure appears only in sectors of the economy that are sensitive to bank financing. Next, to further ensure that the loan supply measure is not a leading indicator of a weakening in aggregate demand, this loan supply proxy is shown to be significant during both expansions and contractions. Finally, borrowing a page from the literature on the identification of monetary policy, it is shown that that part of the loan supply shock that is exogenous to the state of the economy is important. All three tests ensure that our measure of bank health is not serving as a proxy for loan demand or firm health more generally, but captures the effect of shifts in loan supply on the economy.

The study proceeds as follows. The next section describes the empirical design and how it avoids many criticisms of prior studies that examine the credit channel. The second section describes the results obtained from examining how the bank health variable and some variants of that measure influence real GDP and its components. The final section concludes.

I. Empirical Design

The study's empirical design reveals the innovative approach used to identify loan supply shocks in this study. This design is illustrated by a simple equation for the growth in real GDP:

$$GDP_{t+i} = \alpha_0 + \alpha_1 E_t (GDP_{t+i} / \Omega_t) + \alpha_2 LS_t + \varepsilon_t . \quad (1)$$

GDP growth in period t+i is assumed to depend on shocks to loan supply at time t, LS_t, as well as the myriad of other influences contained in the GDP growth forecast made at time t for period t+i, $E_t(GDP_{t+i}/ \Omega_t)$. The inclusion of the forecast in the equation controls for all publicly known information about any demand or supply shocks – such as oil price movements, shifts in labor supply, changes in government spending, or past or expected changes in inflation or interest rates. As a result, the coefficient on the proxy for a loan supply shock in equation 1 is estimated controlling for the important variables that explain the growth in real GDP and, thus, any publicly known information about factors that would cause shifts in loan demand. Further, since any publicly known shock to loan supply will be included in the forecast, α_2 should be capturing the effect on the economy of the unknown, and thus unpredicted, portion of any loan supply shock.

Complicating the matter, the effect of any loan supply shock should spread through the economy over time. Given this gradual effect, one way to test for the impact of loan supply shocks on the economy is simply to use lags of the loan supply proxy in equation 1. Yet such a specification would compound any problem with the possible dissipation over time of the confidentiality of the bank supervisory information that serves as the basis for the loan supply shock proxy. If the effect of the shock takes time to manifest itself in changes in output, simply lagging the loan supply proxy may not show an effect when using the forecast as a control variable, since by the time forecasts are made for the affected quarter, the lagged bank supervisory information may have become known to the forecaster. To avoid this problem, we examine individually the quarterly growth rates for each of the subsequent four quarters following a forecast date; that is, the actual growth rates associated with the one-, two-, three-, and four-quarter-ahead forecasts. If the effect of the shock takes time to manifest itself in macro activity, the effect would be evident in the out-quarters of the forecast errors. Examining this range of forecast horizons allows us to untangle the effect of the loan supply shock from the duration of the confidentiality of the underlying bank health information.

As a result, equation 1 is estimated separately for the one-, two-, three-, and four-quarter-ahead forecasts using the Federal Reserve's own internal forecasts (the Greenbook) and three major commercial forecasters - Data Resources, Inc.-McGraw Hill (DRI), Georgia State University (GSU), and the University of Michigan Research Seminar in Quantitative Economics (RSQE) – from 1978:I, when the data underlying our loan supply shock proxy first becomes available, to 1998:IV. [1] All three private forecasters sell their forecasts commercially and have generally been among those with the best forecast record for the macroeconomic variables examined in this study (McNees 1992). Each forecaster makes at least one forecast each quarter; when a forecaster makes more than one forecast in a given quarter, the one closest to the others is selected so that all forecasts contain roughly the same information set.

The proxy for the loan supply shock is based on the confidential CAMEL ratings used by bank examiners to rate individual banks. [2] The composite CAMEL scores given to banks are based on the five categories supervisors analyze when evaluating the health of a bank: Capital, Assets, Management, Earnings, and Liquidity.[3] Each bank is rated from 1, the highest, to 5, the lowest, on each of the component categories and given a composite rating. Banks with a CAMEL rating of 5 (high probability of failure, severely deficient performance) represent the set of banks with the most severe problems. The measure of bank health data used here is the share of assets with a CAMEL rating of 5, measured as a percentage of the total assets of all commercial and savings banks with a supervisory rating. We use the value for the end of the month prior to the forecast, for example, January 1990 for forecasts made in February 1990.

Figure 1 presents the share of bank assets in institutions with a CAMEL rating of 5 (CAMEL5) through time. Although the series exhibits fairly significant persistence, it appears to follow a slow mean-reverting process with reflecting boundaries. Figure 1 shows that on several occasions CAMEL5 increased substantially and then receded, for example, during and after the farm problems in the Midwest, the oil price declines for the Southwest, and the real estate price declines in the Northeast. That the sharp increases in CAMEL5 were temporary should not be surprising, since banks with a CAMEL rating of 5 must either fail or be upgraded as they recover. Thus, there is ample reason to believe that the CAMEL5 variable is mean reverting with a low mean value.

Bank behavior is strongly related to this measure of bank health, with the growth in loans and assets being highly correlated with the supervisory rating assigned to the bank. Banks with CAMEL ratings of 1 or 2 exhibit quarterly loan and asset growth rates of about 2 percent. Banks with a CAMEL 4 rating exhibit loan and asset shrinkage of about the same magnitude as the growth shown by the group of CAMEL 2-rated banks. However, the shrinkage pattern exhibited by those banks with the lowest rating, CAMEL 5, deviate substantially from the symmetric pattern around the CAMEL 3 rating, with quarterly shrinkage rates averaging over 4 percent for assets and about 5 and 7 percent for total loans and commercial and industrial loans, respectively.

Figure 2 shows that it is *having* a CAMEL 5 rating rather than *getting* a CAMEL 5 rating (i.e., being downgraded) that affects bank behavior. The figure presents the average quarterly loan growth rate from three quarters before through three quarters after banks receive downgrades of their CAMEL rating. Not only do downgrades to a CAMEL 5 rating have a large impact on loan growth during the quarter the bank is downgraded, but banks continue to shrink significantly even three quarters after the downgrade occurs. This result makes sense, since a bank cannot immediately shrink to its new desired size. Furthermore, CAMEL 4-rated banks behave the same whether that CAMEL rating is in effect before or after a downgrade, and the same is true for CAMEL 3-rated banks. Thus, estimating the regression with the level of the bank health variable seems to be the superior specification, although the last section of the study shows that using an estimate of the surprise component of the measure provides similar results.

Finally, the error term in equation 1 is not assumed to be independent and identically distributed. All forecasters tend to miss major macroeconomic surprises, producing errors that exhibit contemporaneous correlations across forecasters. Furthermore, since such macro surprises sometimes occur late in the forecast horizon, the errors could be correlated across time. We use procedures suggested by Keane and Runkle (1990) to address the potential problems with inconsistent estimates of coefficient standard errors caused by these contemporaneous and intertemporal cross-correlations in the error term.[4] The potential correlations in the errors also dictate the way the forecasts are lined up. Since several of the forecasts are published only toward the middle of each quarter, while others are produced monthly, we use the monthly forecast from the middle month of each quarter.[5] This timing convention also ensures that all the forecasters know the U.S. Bureau of Economic Analysis (BEA) preliminary estimate of GDP for the prior quarter at the time the forecasts are made, eliminating the potential for a moving average process in the errors of the one-quarter-ahead forecasts.[6]

Table 1 provides the results from estimating equation 1 for real GDP growth from 1978 through 1998. The coefficient on the proxy for loan supply shocks is estimated for each of the four one-quarter forecast horizons separately. The estimated coefficient on the bank health variable is negative for each of the four quarters, as expected, and statistically significant for the first two quarters. The estimated coefficients imply that as bank health deteriorates (the percentage of bank assets in CAMEL 5-rated banks increases), forecasters tend to overpredict real GDP – that is, GDP growth weakens (relative to its forecasted value) with an adverse shock to loan supply. The estimated coefficients are also of economic significance. For example, a one-standard-deviation increase in CAMEL5 lowers actual GDP growth by 0.6 to 0.8 of a percentage point from what was expected in each of the first two quarterly forecasts. Since that pattern is not reversed during the subsequent two quarters, the level of real GDP remains permanently lower throughout the forecast horizon.

II. Identification of Loan Supply Shocks

In a study examining the usefulness and impact of bank supervisory information on monetary policy, Peek, Rosengren, and Tootell (1999) present results consistent with those in Table 1 for forecast errors of the unemployment and inflation rates. Although using forecasts is a more effective way to control for loan demand, and using supervisors' ratings of bank health is a cleaner proxy for shocks to loan supply that are independent of shifts in loan demand, the significance of the CAMEL5 variable in either the GDP equation in Table 1 or the unemployment and inflation rate equations in Peek, Rosengren, and Tootell (1999) still could be interpreted as suggesting that a deterioration in bank health is simply serving as a leading indicator of future weakness in the economy, and not that the state of bank health is causally related to economic activity. Specifically, the information on deteriorating bank health contained in CAMEL5 could indicate a weakness of the firms that borrow from banks, rather than a decline in the proclivity of banks to lend. Thus, even though the forecast of GDP is controlling for the shocks to loan demand on average, the errors in the forecasts that are correlated with the bank health variable may represent instances when forecasters make a mistake about the strength of loan demand. High values of the bank health variable (weak bank health) may still be serving as a proxy for times when the economy, and loan demand, is unexpectedly weak.

Examining Components of GDP

To ensure that CAMEL5 is capturing loan supply effects, we begin by investigating the effect of the bank health variable on the major components of GDP. This decomposition helps identify the nature of the CAMEL5 effect by testing whether the importance of the loan supply shock variable for GDP growth originates in components of real GDP for which bank lending is a significant source of financing. If the bank health variable is, in fact, capturing the effect on the forecast errors of shifts in loan demand, then the loan demand shocks could come from any component of GDP, whether or not that component was related to the activities of bank-dependent firms. If the loan supply proxy is capturing loan demand effects, or is simply serving as a leading indicator of changing economic conditions in general, then the effect should be widespread across components of GDP, especially endogenous components such as consumption. If the proxy is capturing shocks to bank lending, it should directly affect the sectors for which bank lending is important, and might have little effect on components not very reliant on bank financing.

The effect of the proxy for loan supply shocks on the major components of real GDP is examined using the forecasts of these components as control variables for all publicly known demand and supply shocks relevant to that sector. Table 2 presents the estimated coefficients on the loan supply proxy from these regressions. If the proxy variable is capturing only loan supply shocks, then the components should differ in their sensitivity to problems in the banking sector. In that case, the change in inventory investment should be the component that is most sensitive to loan supply shocks. Banks are crucial for inventory financing for both small and large firms; small firms have few substitutes for short-term credit from banks, and even large firms have limited alternative sources of inventory financing, insofar as insurance company and finance company lending tends not to be short-term, unsecured credit (Himmelberg and Morgan 1995). In fact, several studies have found an association between bank lending and inventory investment (Kashyap, Stein, and Wilcox 1993; Kashyap, Lamont, and Stein 1994). The least sensitive sector should be government spending.

The first row of Table 2 presents the estimated coefficients on the loan supply variable for the change in business inventories for each of the four forecast horizons. The coefficients are negative, as expected, and statistically significant at each forecast horizon, consistent with the hypothesis that an adverse shock to loan supply (a higher value of CAMEL5) makes it more difficult for firms to obtain loans to finance inventories. Thus, when adverse loan supply shocks occur, forecasters tend to overpredict the change in business inventories. Since inventory movements account for much of the fluctuation in GDP (Ramey 1989; Blinder and Maccini 1991), they are critical for understanding the importance of banks to real economic activity.

The relationship between loan supply shocks and the other components of GDP should be much weaker. Investment is the next most likely candidate for a loan supply effect. The estimated coefficients for the loan supply proxy in the nonresidential fixed investment regressions, while always correctly signed, are not significant for any of the four forecast horizons. In part, this result may be related to the importance of nonbank sources, such as insurance companies and pension funds, for financing nonresidential structures. For the investment in producers' durable equipment subcomponent, the estimated coefficients are correctly signed but are significant at the 10% level only for the second- and third-quarter-ahead specifications. These results are consistent with previous findings of a lack of a clear relationship between equipment investment and bank lending, perhaps in part because much of the investment in producers' durable equipment is undertaken by large firms that have easy access to sources of financing other than banks. The effect is not robust for residential investment either, as the estimated coefficient on the proxy for loan supply shocks is insignificant at each horizon. As Edwards and Mishkin (1995) point out, the ascension of the secondary mortgage market, which includes nonbank lenders, should reduce the importance of bank lending for residential investment.

Similarly, a number of factors suggest that consumer spending may not be particularly sensitive to shocks to bank lending. Consumer lending for durable goods can occur through financing by the producer or one of its affiliates (such as GMAC), as well as through bank lending. The other major source of consumer credit is credit cards. This market is highly liquid and national in scope. Furthermore, the personal tax deduction for consumer interest is now allowed only for real estate loans, so consumer borrowing occurs more and more in the form of mortgage credit, which is increasingly tied to the secondary mortgage market. In fact, Table 2 provides little evidence that consumer spending is affected by loan supply shocks generated by changes in bank health. The estimated coefficient on the proxy for loan supply shocks is insignificant at each horizon.

Perhaps surprisingly, Table 2 presents some mild evidence that loan supply shocks adversely affect exports, with three of the four estimated coefficients significant at the 10 percent level. A possible explanation is that the export business relies heavily on banks, with letters of credit and other credit enhancements frequently used in foreign trade being serviced primarily by internationally active banks, including those in the United States.

Finally, one would expect that government spending would not be susceptible to a loan supply shock. Since the government tends to purchase goods, such as weapons, from companies that are too big to be deemed bank dependent, and labor services from the public, this sector should be relatively immune to disturbances to loan supply. Table 2 shows no evidence that loan supply shocks affect government spending; the estimated coefficient on the bank health variable is insignificant at each horizon.

The pattern of effects for the components of GDP provides strong evidence that the bank health variable is not simply correlated with demand errors in the forecasts. If the estimated effect derived from either aggregate demand generally or loan demand in particular, one would expect the effect to appear more broadly across the various GDP components, particularly in the more endogenous components. On the other hand, if the effect emanates solely from loan supply shocks, one would be more likely to find it only for the components that rely most heavily on bank financing, as is the case here. These results suggest that the bank health variable has isolated a loan supply effect, and that this loan supply shock has important effects on economic activity.

Cyclicality of the Effect

Even though the variable measuring bank health affects only bank-dependent sectors of the economy, the variable might still be capturing a hidden demand effect. It is possible that firms hit first by a downturn in demand also tend to disproportionately hold inventories, and that forecasters tend to miss these turning points in economic activity. If bank health weakens significantly at turning points because of the decline in the economy's strength, and the forecasters are unaware of the extent of any deterioration in bank balance sheets due to the confidentiality of the supervisory data, then bank health may still be acting as a leading indicator of the downturn rather than as a causal driver. However, this explanation requires forecasters to systematically overpredict output growth in a recession and/or systematically underpredict economic activity in a boom. Both possibilities can be tested easily by examining the stability of the effect of the loan supply proxy on the economy across the different phases of the business cycle. Since Table 2 shows that the effect is centered in business inventories, we report results only for that component of GDP.

In fact, systematic cyclical errors do not explain the significance of bank health in these regressions. Over the full sample, the forecasts are not biased; the constant term is not significantly different from zero when the bank health variable is omitted.[7] Still, the concern is that forecasters systematically overpredict economic activity as the economy slips into recession, with these systematic errors correlated with bank health. To ensure that the results in Table 2 are not simply an artifact of possible cyclical errors in forecasts, we test whether the estimated coefficient on our measure of bank health is significant only during recessions. Table 3 presents the results for the change in business inventories using a specification similar to that in Table 2, but including two additional explanatory variables: a (0,1) dummy variable with a value of one when the economy is in a recession and an interactive variable equal to the product of the recession dummy variable and the bank health variable. Using the NBER peak and trough dates, the recession quarters are selected based on the quarter of the actual values, not on the quarters in which the forecasts are made. The different constant term allows the forecasts of inventories to miss in a systematic way during recessions, while the different slope coefficient tests whether the loan supply shock proxy affects the economy differently during downturns. If the forecasts tend to miss on the upside during recessions and on the downside during expansions, then this specification helps to ensure that any possible short-run bias does not contribute to the significance of the estimated coefficient on bank health.

The results in Table 3 clearly indicate that poor bank health has a negative effect on the change in business inventories, regardless of the state of the economy. The insignificant estimated coefficient on the recession differential for the bank health variable indicates that one cannot reject the hypothesis that the effect of the loan supply proxy is identical whether the economy is expanding or contracting. Furthermore, although the estimated effect of the recession dummy variable is negative, it is never statistically significant. While the inclusion of the confidential data makes interpretation of this coefficient difficult, Table 3 provides little evidence that the forecasters tend to systematically overpredict economic activity during recessions.

Still, the recession dummy variable in Table 3 might be too blunt an instrument to control for possible systematic cyclical errors in the forecasts**.** For example, bank health might be an important leading indictor of economic weakness at turning points, rather than during recessions. To examine such a possibility, Table 4 presents results for equations estimated over only that part of the sample when the economy was booming – i.e., when it was growing faster than its potential. If the bank health variable has successfully isolated the effects of a loan supply shock, then the negative effect on economic activity of poor bank health would be observed even when loan demand was relatively high. In fact, the estimated coefficient on the proxy for loan supply shocks is correctly signed and statistically significant at each forecast horizon. The bank health variable is not simply capturing a bias over this subsample, since the forecasts do not make systematic errors over this period - the constant term does not differ significantly from zero when the equation is estimated without the bank health variable. Thus, even in periods of strong loan demand, an adverse loan supply shock weakens business inventory investment. In short, Tables 3 and 4 provide strong evidence that the bank health proxy is not simply a leading indicator of future economic activity, but a causal driver of that activity. The tables also reveal that the results are not derived solely from one or two periods characterized by weak demand and weak bank health.

Orthogonalized Loan Supply Shocks

In this section, a simple two-step estimation framework is used to create a measure of the loan supply shock that is orthogonal to the state of the economy. The first step estimates a specification with CAMEL5 being a function of the state of the economy. The fitted component of this regression represents that part of bank health that is correlated with macroeconomic activity, while the residual is that part of CAMEL5 that is orthogonal to macroeconomic activity. The effect of that orthogonalized measure of bank health on GDP and its major components is then examined.

The first-stage regression specifies the bank health measure as a function of the known state of the economy,

$$\text{CAMEL5}_t = \alpha_0 + \alpha_1 X_t + \varepsilon_t, \tag{2}$$

where $\forall_1$ is a vector of coefficients for the variables in X. The set of potentially appropriate right-hand-side variables in this equation must satisfy the criterion that they are known to the public at time t, ruling out measures such as lagged values of the confidential loan supply shock variable and the contemporary forecast errors for GDP. The set of variables used is fairly exhaustive in order to ensure that the residual term is not simply the value of CAMEL5.[8] In fact, the R^2 on this first stage equation is almost 50 percent. The exogenous part of the loan supply proxy, ε_t, is then used to estimate second-step equations of the form

$$GDP_{t+i} = \beta_0 + \beta_1 E_t(GDP_{t+i} / \Omega_t) + \beta_2 \varepsilon_t + \eta_t. \tag{3}$$

The results of this second stage estimation are presented in Table 5. As with Tables 1 and 2, the estimated coefficients on the loan supply proxy, $\exists_2$, are presented for GDP and its major components for each of the four forecast horizons. This orthogonalization of the loan supply shock produces results consistent with those in the first two tables. The estimated coefficient on the orthogonalized loan supply proxy in the GDP equation is negative for all four quarters, statistically significant for the second quarter, and just misses significance at the 5 percent level for the first and third quarters. The estimated coefficient is significant at each horizon in the inventory regression. There is also some evidence of an effect in two other sectors where bank lending might be important, exports and nonresidential investment. The loan supply variable fails to affect the other sectors of the economy where bank lending would not be important, such as government spending. These results tell the same story as those in Table 2.

The importance of the loan supply shock is robust to alternative specifications of the first-step equation. For example, including the GDP forecast error in the estimation of either the first or second stage regression results in similar findings. Including these forecast errors ensures that the significance of the loan supply shock is not due to errors in the GDP forecast in general. However, this is a particularly stringent test, since it assumes information that the agents do not possess, specifically, the future realizations of output growth. Even so, the residuals from the first-step equation remain significant in the second-step inventory regressions. In fact, including all of these variables together produces similar results. Thus, the importance of the loan supply shock is robust to alternative measures of the shock.

III. Conclusion

The evidence in this study provides compelling new support for the hypothesis that the credit channel is operative in the U.S. economy, and that loan supply shocks have had a significant impact on real macroeconomic variables over the past two decades. Using a variable that directly measures bank health, and, in particular, that part of the bank health measure that is unknown to the public and orthogonal to the state of the economy, rather than a proxy for monetary policy shocks, allows a cleaner identification of loan supply shocks. Using forecasts of economic activity better controls for loan demand. That the importance of the bank health variable is strongest in the component of real GDP that is most bank dependent, the change in business inventories, and that the effect is not widespread across the major components of GDP suggest that the contribution of this variable does, in fact, derive from its role as a measure of shocks to loan supply, rather than as a leading indicator of demand shocks to the economy as a whole, or to loan demand in particular. That the effect of the bank health variable is significant even when loan demand is strong or the exogenous part of CAMEL5 is used indicates that this variable has successfully isolated loan supply shocks from those to loan demand.

These results have several implications. The first concerns the debate about the mechanism underlying the credit channel. Balance sheet effects, which manifest themselves through changes in asset prices and interest rate spreads, are incorporated in the forecasts used in this study as control variables, since information about the state of these pressures is readily available in the marketplace. Thus, the importance of the bank health variable in this study suggests that a credit channel working through something other than interest rate differentials, or the level of the federal funds rate for that matter, is at work here. The results also show where that impact is largest, on business inventory investment, an area that previous research has indicated would be the component of GDP likely to be most affected by problems in the banking sector. In fact, the results suggest that some of the unexplained movement in inventories can be attributed to the effect of the credit channel, as hypothesized by Ramey (1993). Finally, the results reinforce the idea that the health of the banking sector must be considered when either charting the expected course of the economy or calculating the effects of monetary policy. These lessons may be even more relevant to policymakers in countries where the banking system plays a more important role in credit allocation. This last fact highlights why the International Monetary Fund and the World Bank have recently emphasized the importance of maintaining a healthy banking system.

Table 1
CAMEL5 and Forecast Errors for Real GDP

Variable	Q1	Q2	Q3	Q4
Constant	1.557**	1.765**	1.568*	1.796*
	(4.02)	(3.06)	(2.25)	(2.40)
Forecast	0.908**	0.757**	0.755**	0.416
	(10.20)	(4.99)	(3.73)	(1.96)
Bank Weakness	-0.626*	-0.771*	-0.718	-0.145
	(2.38)	(2.01)	(1.53)	(0.30)
Observations	334	330	326	322
Adjusted R^2	0.518	0.209	0.133	0.029

Note: The coefficient standard errors are corrected for the appropriate moving average error terms and for contemporaneous correlation across forecasters. Absolute values of t-statistics are in parentheses.

** Significant at the 1 percent level.
* Significant at the 5 percent level.

Table 2
Estimated Bank Health Effects for Major Components of Real GDP

Variable	Q1	Q2	Q3	Q4
Change in Business Inventories	-7.124**	-8.120**	-9.673**	-11.138**
	(3.50)	(3.20)	(3.31)	(3.56)
Nonresidential Investment	-.789	-1.821	-1.641	-.798
	(.88)	(1.53)	(1.19)	(.51)
Producers' Durable Expenditures	-1.482	-2.716	-2.370	-1.255
	(1.14)	(1.86)	(1.71)	(.65)
Residential Investment	.166	-1.373	1.007	3.215
	(.13)	(.60)	(.35)	(1.10)
Consumption	-.234	-.182	-.004	.253
	(.94)	(.68)	(.01)	(.75)
Exports	-2.067	-2.389	-2.474	-2.260
	(1.67)	(1.78)	(1.77)	(1.58)
Government	.319	-.062	-.184	.158
	(.55)	(.11)	(.44)	(.44)

Note: The coefficient standard errors are corrected for the appropriate moving average error terms and for contemporaneous correlation across forecasters. Absolute values of t-statistics are in parentheses.

** Significant at the 1 percent level.
* Significant at the 5 percent level.

Table 3
The Business Cycle Sensitivity of the Bank Health Effect on Changes in Business Inventories

Variable	Q1	Q2	Q3	Q4
Constant	14.099**	14.111**	16.678**	17.588**
	(3.85)	(3.13)	(3.15)	(3.26)
Forecast	.700**	.739**	.713**	.729**
	(7.77)	(6.40)	(4.86)	(4.68)
Bank Weakness	-7.329**	-8.118**	-10.289**	-11.530**
	(3.29)	(3.06)	(3.46)	(3.82)
Recession	-11.051	-11.045	-16.391	-16.233
	(1.38)	(1.22)	(1.68)	(1.65)
Bank Weakness ✕ Recession	1.049	-1.618	-1.049	-5.723
	(.21)	(.26)	(.14)	(.66)

Note: The coefficient standard errors are corrected for the appropriate moving average error terms and for contemporaneous correlation across forecasters. Absolute values of t-statistics are in parentheses.

** Significant at the 1 percent level.
* Significant at the 5 percent level.

Table 4
The Effect of Bank Health on the Change in Business Inventories During High Growth Periods

Variable	Q1	Q2	Q3	Q4
Constant	15.343**	14.819**	17.968**	17.823*
	(3.45)	(2.78)	(2.93)	(2.54)
Forecast	.777**	.825**	.788**	.835**
	(6.96)	(5.98)	(4.49)	(4.07)
Bank Weakness	-8.685**	-7.958*	-11.162**	-11.416**
	(2.97)	(2.41)	(2.95)	(2.83)

Note: The coefficient standard errors are corrected for the appropriate moving average error terms and for contemporaneous correlation across forecasters. Absolute values of t-statistics are in parentheses.

** Significant at the 1 percent level.
* Significant at the 5 percent level.

Table 5

Effect of ε_t on Major Components of Real GDP

Variable	Forecast Horizon			
	Q1	Q2	Q3	Q4
Gross Domestic Product	-0.694	-1.359**	-1.106	-0.333
	(1.82)	(2.61)	(1.88)	(0.53)
Change in Business Inventories	-7.242**	-9.192**	-9.232*	-12.162**
	(2.78)	(2.86)	(2.29)	(2.91)
Nonresidential Investment	-1.074	-4.260**	-3.014	-1.722
	(0.88)	(2.80)	(1.77)	(0.90)
Residential Investment	-1.756	-4.461	-1.203	4.517
	(0.97)	(1.56)	(0.33)	(1.16)
Consumption	-0.367	-0.650	-0.285	0.180
	(1.05)	(1.63)	(0.62)	(0.38)
Exports	-2.152	-3.996*	-4.302*	-3.705*
	(1.24)	(2.22)	(2.41)	(1.97)
Government	0.697	0.679	-0.383	-0.330
	(0.86)	(0.86)	(0.50)	(0.43)

Note: ε_t is the residual of the regression of CAMEL5 on leading economic indicators (lags of GDP components, growth of money supply, commercial paper-treasury bill spread, consumer expectations, consumer sentiment, and initial claims for unemployment insurance). The coefficient standard errors are corrected for the appropriate moving average error terms and for contemporaneous correlation across forecasters. Absolute values of t-statistics are in parentheses.

** Significant at the 1 percent level.
* Significant at the 5 percent level.

Figure 1
Percentage of Assets in CAMEL-5 Rated Banks

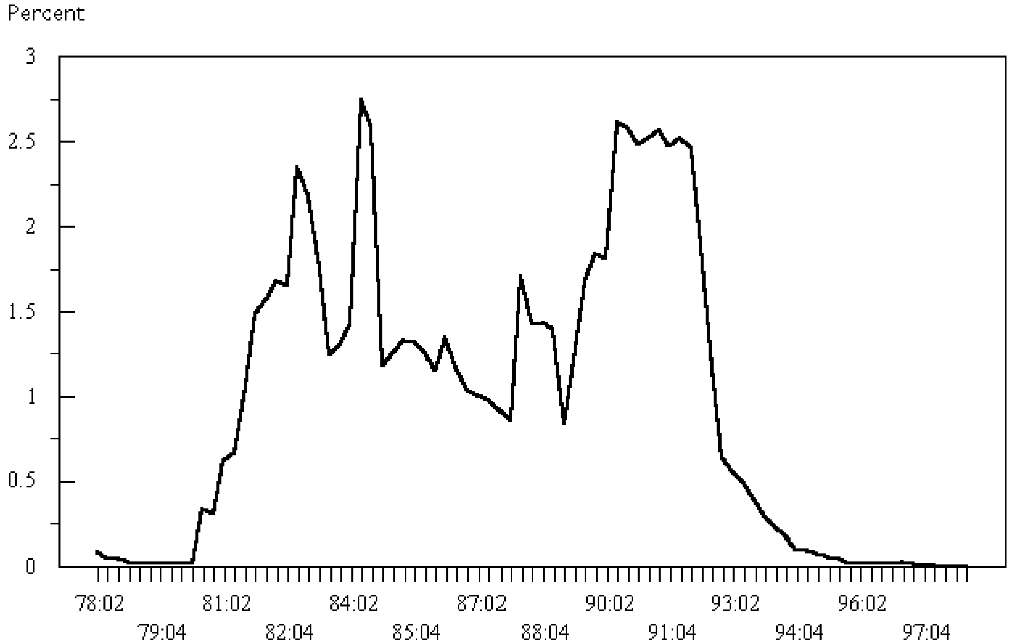
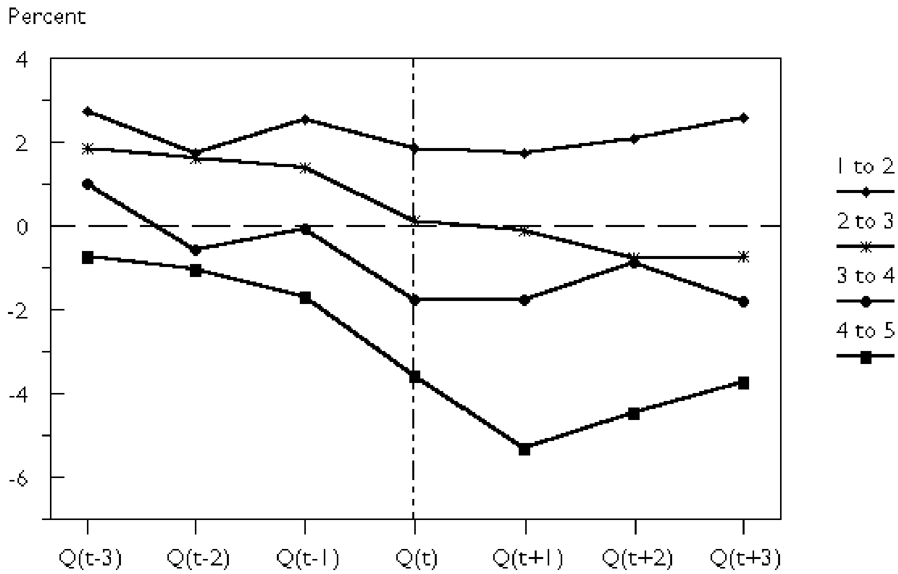


Figure 2
Loan Growth Around CAMEL Downgrades



Note: Q(t) is the quarter of the downgrade.

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Endnotes

1. Thus, the estimation is conducted using a panel data set, although the results are essentially unchanged if the estimation is performed forecaster by forecaster. The data set is unbalanced since RSQE is missing the 1978:II and 1979:II observations, and the Greenbook forecasts for nonresidential investment, producers' durable expenditures, residential investment, and consumption begin in 1978:III, and in 1986:I for the change in business inventories and exports.
2. Since efficient forecasts would include observable loan supply shocks, it is important to identify loan supply shocks that are unobservable to the public. For these tests to work, the supervisory data must be confidential. Peek, Rosengren, and Tootell (1999) show that publicly available information on the banking sector did not improve on forecasts of inflation and unemployment rates, while the confidential CAMEL ratings did. Other empirical work also supports the conclusion that some of the information contained in the CAMEL ratings is not known by the private sector (for example, Berger, Davies, and Flannery 2000; DeYoung, Flannery, Lang, and Sorescu 1998).
3. On January 1, 1997, the CAMEL rating system was expanded to CAMELS. The S stands for "sensitivity to market risk" and is intended to measure how well prepared a bank is to handle changes in interest rates, exchange rates, and commodity or equity prices.
4. The covariance matrix is constructed from estimates of the contemporaneous cross-correlations among the different forecasters and any moving average in the errors that might occur across different horizons of the forecast.
5. The final GDP estimate before the benchmark revisions is used. Using this measure assumes that forecasters are predicting the actual underlying activity rather than trying to forecast any

of the preliminary estimates based on more incomplete data. There were two benchmark revisions during our sample, 1986:I and 1992:I. This poses a potential problem because at the time of the benchmark, some of the forecasts are based on the old benchmark, while actual GDP as reported by the BEA is reported using the new benchmark. However, the major results reported in this paper are not sensitive to the exclusion of those observations.

6. For example, for the February forecast date, the one-quarter-ahead forecast would be for the period from January 1 to March 31. At that time, all the forecasters would have the BEA's advance estimate of GDP for the previous quarter.

7. It is inappropriate to test for forecast bias by examining the constant term when information unknown to the forecasters at the time the forecasts were made is included in the regression equation. Even if the constant term is significantly different from zero, the forecasts could still be unbiased, since the constant term becomes a convolution of the forecast's bias, the estimated coefficient of the proxy for bank health, and the value of CAMEL5 that has a neutral effect on the economy.

8. A broad set of variables is used when estimating this regression, including two lags of the various components of GDP, financial variables such as the federal funds rate, M2 growth, and the spread between rates on commercial paper and treasuries, as well as leading and current indicators of economic activity, such as consumer confidence and expectations, and the level of initial unemployment claims.