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The Effect of Monetary Policy on Bank Lending and Aggregate Output: Asymmetries from Nonlinearities in the Lending Channel

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This paper examines the asymmetric effects of monetary policy on output and the role of bank-lending behavior. We investigate whether contractionary and expansionary policies have asymmetric impacts on bank loans, and whether there are further differences in the response of small banks and big banks to policy actions. We also investigate the link between changes in bank lending and aggregate economic activity. Our goal is to simultaneously capture the existence of the lending view of the monetary transmission mechanism, the strong relationship between loan growth and output growth, and the asymmetric effect of monetary policy on output. We use a nonlinear vector autoregressive approach to carry out our analysis. Our results show that asymmetry in the response of bank lending to monetary policy is not a substantially contributing factor in explaining the different responses of output to contractionary and expansionary policy.

Key Words: Bank Lending; Monetary Transmission Mechanism; Asymmetries; Smooth Transition Regression; Cointegration.
JEL Classification Numbers: C32, E52, G18.

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1. INTRODUCTION

A number of theoretic and empirical studies have provided evidence on asymmetric effects of monetary policy on output.[1] In theory these asymmetries can arise from a convex aggregate supply curve, such as menu cost model and wage indexation. They also can arise on the aggregate demand side due, for example, to credit rationing constraints or a liquidity trap. Over the past decade the literature on the bank lending channel has promoted the role of banks in the monetary transmission mechanism. This so-called lending view stresses that the asymmetry of the loan response to policy, as arising due to differences in bank balance sheet strength, which is commonly characterized by bank asset size or bank capital. Using micro banking data disaggregated into different bank-size categories, Kashyap and Stein (1995) argue that the sensitivity of loans to changes in monetary policy is related to bank size. Loans of big banks, whose borrowers have greater access to national credit markets, have greater sensitivity to changes in monetary policy than loans at smaller banks. Focusing on different responses between capital-constrained and unconstrained banks, rather than between big and small banks, Peek and Rosengren (1995) examine why the magnitudes of the effect of monetary policy are likely to be weakened when banks face binding capital constraints. Kishan and Opiela (2000) emphasize that the loan growth of small, undercapitalized banks is more responsive to changes in monetary policy than loan growth at lager and better-capitalized banks. Despite the theoretical arguments regarding loan asymmetry, empirical studies have not explicitly investigated many of these issues. Although empirical studies have measured the effects of policy on loans over the entire business cycle, they fail to differentiate between the effects of expansionary and contractionary policy on bank loans for banks of different sizes.[2]

The main purpose of this paper is to explore whether bank-lending behavior can provide a convincing explanation for the asymmetric effect of monetary policy on output. We investigate whether contractionary and expansionary policies have asymmetric impacts on bank loans, and whether there are further differences in the response of small banks and large banks to policy actions. We also investigate the link between changes in bank lending and aggregate economic activity. Note that the Commerce Department tracks loan growth because it is a coincident indicator of output growth, and studies by Walsh and Wilcox (1995) and Friedman and

[1]See Ball and Mankiw (1994), Cover (1992), De Long and Summers (1988), Karras (1996a, 1996b), Morgan (1993), Ravn and Sola (1996), Rhee and Rich (1996), Weise (1999), and Kandil (2000).

[2]See Kashyap and Stein (1995), Kishan and Opiela (2000) and Peek and Rosengren (1995).

Kuttner (1993) show a strong relationship between loan growth and GDP growth. To carry out our analysis, we use a nonlinear vector autoregressive approach to simultaneously capture the existence of the lending view of the monetary transmission mechanism, the strong relationship between loan growth and output growth, and the asymmetric effect of monetary policy on bank loans and output. To emphasize differences in banks asset size as indicators of balance-sheet strength, we aggregate the Call Reports data over the period 1976Q1-1999Q3. Our results show that asymmetry in the response of bank lending to monetary policy is not a substantially contributing factor in explaining the different responses of output to contractionary and expansionary policy.

The remainder of the paper is organized as follows. Section 2 identifies a nonlinear smooth transition vector error-correction model. Section 3 describes the details of the data and estimation results. Section 4 provides the investigation of the asymmetries by computing the generalized impulse response functions. The final section draws the conclusions and some remarks.

2. MODEL SETUP

2.1. Setup of the Benchmark Model

The vector autoregression model (henceforth, VAR) is widely used as a convenient method to capture the simultaneous dynamic relationships among a set of variables. Once estimated, a VAR can be used to simulate the response over time of the dependent variables to shocks to the disturbances in any or all of the equations.

Our VAR system has four endogenous variables, including the log of real big-bank loans (BL), the log of real small-bank loans (SL), the log of real gross domestic product (Y), and the real federal funds rates (RFR). The data used to construct these series will be described in a later section. Based on statistical tests we cannot reject the null hypothesis that our four series each have a unit root. We then test for cointegration, and finding cointegration we model our series with a vector error-correction model (henceforth, VECM). The VECM provides information about the short run dynamics as well as the long-run relationship among the variables.

Our benchmark model can be written as:

$$DX_t = A_0^0 + \sum_{p=1}^{n} A_{1p}^0 * DX_{t-p} + A_2^0 * EC_{t-1} + E_t^0, \tag{1}$$

where $DX_t = (DBL_t, DSL_t, DY_t, DRFR_t)'$, and the error-correction term is EC_t.

2.2. Smooth Transition Model

The main purpose of this paper is to examine asymmetries in the effects of expansionary and contractionary monetary policy on bank lending and aggregate output. We are therefore interested in a nonlinear model, one that allows different regimes in response to changes in monetary policy. Granger and Teräsvirta (1993) summarize a wide variety of nonlinear models, including regime-switching models for time series. Regime-switching models can be classified into two general categories.[3] One is the smooth transition regression (henceforth, STR) model,[4] which assumes that the variable defining a regime is observable. The other is the Markov regime-switching regression model, which assumes that a regime (or state of the world) is not known with certainty but that the probabilities of being in each regime and of transitioning between regimes can be estimated. We use the STR model here, because the monetary policy variable that defines the state of the world is observable.

Broadly speaking, the STR model can be expressed as:

$$\begin{aligned} DX_t &= A_0 + A_1 * DX_{t-1} + A_2 * EC_{t-1} \\ &+ (B_0 + B_1 * DX_{t-1} + B_2 * EC_{t-1}) * F(z_{t-d}) + E_t, \end{aligned} \tag{2}$$

where $F(z_{t-d})$ is the transition function, a continuous function of the transition variable z_{t-d} and bounded between zero and unity. The transition function can be specified as either

$$F(z_{t-d}) = (1 + \exp\{-\gamma(z_{t-d} - k)/\sigma_z\})^{-1}, \quad \text{where} \gamma > 0 \tag{3}$$

or

$$F(z_{t-d}) = 1 - \exp\{-\gamma(z_{t-d} - k)^2/\sigma_z^2\}, \quad \text{where } \gamma > 0. \tag{4}$$

If the function F is defined by equation (3), the corresponding model is called the logistic STR model. It is called the exponential STR model if F is defined by equation (4). The value of the function F will depend on the deviation between the value of the transition variable z_{t-d} and the threshold value k, and on the smooth transition parameter γ which governs the rate of adjustment between the two regimes. The standard deviation of the transition variable σ_z facilitates our estimation of γ.

[3]The properties and application of these two categories in modeling financial variables are discussed in detail by Franses and Van Dijk (2000).

[4]The threshold models can be considered as a special case of STR models. Chan and Tong (1986); Lüukkonen, Saikkonen and Teräsvirta (1988); Teräsvirta and Anderson (1992) and Tersvirta (1994, 1998) introduced the STR models in a univariate (or autoregressive) version. Granger and Teräsvirta (1993) and Weise (1999) extend these models to a multivariate context.

As the value of the function F approaches zero, the dynamics of the model are generated only by the A_i in equation (2), but as the value of the function F approaches one, the dynamics are captured by both the A_i and B_i. This is emphasized if we rewrite equation (2) as:

$$\begin{aligned} DX_t &= (A_0 + B_0 * F(z_{t-d})) + (A_1 + B_1 * F(z_{t-d})) * DX_{t-1} \\ &+ (A_2 + B_2 * F(Z_{t-d})) * EC_{t-1} + E_t. \end{aligned} \tag{5}$$

2.3. Testing for Appropriateness of Linearity and Identifying the Nonlinear VECM

Before attempting to specify and estimate our nonlinear VECM, we check whether or not a linear model would suffice. We use a multivariate version of Granger and Ter?svirtas (1993) test for linearity based on a third-order Taylor expansion. The alternative hypothesis is nonlinearity, and the test is based on the following representation:

$$\begin{aligned} DX_t &= A_0 + A_1 * DX_{t-1} + A_2 * EC_{t-1} \\ &+ \sum_{j=1}^{3} (B_{0j} + B_{1j} * DX_{t-1} + B_{2j} * EC_{t-1}) * z_{t-d}^{j} + E_t, \end{aligned} \tag{6}$$

where z_{t-d} is from a set of potential transition variables. The null hypothesis is H_0: $B_{0j} = B_{1j} = B_{2j} = 0$, where $j = 1, 2$ and 3.

In order to decide between the logistic STR and exponential STR model, we test a sequence of sub-hypotheses:

H_{0a}: $B_{03} = B_{13} = B_{23} = 0$,

H_{0b}: $B_{02} = B_{12} = B_{22} = 0$ given $B_{03} = B_{13} = B_{23} = 0$, and

H_{0c}: $B_{01} = B_{11} = B_{21} = 0$ given $B_{02} = B_{12} = B_{22} = B_{03} = B_{13} = B_{23} = 0$.

This specification procedure works as follows. If H_{0a} is rejected, choose a logistic STR model. If H_{0a} is not rejected but H_{0b} is rejected, choose an exponential STR model. If both Hoa and H_{0b} are not rejected but H_{0c} is rejected, then choose a logistic STR model. This decision rule can be sensibly made if the null of linearity is rejected.

In a small sample case, for each equation with each possible transition variable, we calculate F-statistics as $F = [(RRSS - URSS)/(3p(q+1))]/[URSS/(T - 4p(q+1) - 1)]$, where T is the number of the available observations, p is the lag length, q is the number of endogenous variables, and $RRSS$ and $URSS$ are residual sum of squares from the restricted and unrestricted regressions, respectively. However, this test is not strictly appropriate in the system as a whole. Instead we can calculate log-likelihood ratios. Let $\Omega_u = \sum \hat{u}_t \hat{u}_t{}'/T$ and $\Omega_\nu = \sum \hat{\nu}_t \hat{\nu}_t{}'/T$ be the estimated variance-covariance matrices of residuals from the restricted and unrestricted models, respectively. Then we calculate log-likelihood ratios as $LR = T\{\ln|\Omega_u| - \ln|\Omega_\nu|\}$ which are asymptotically distributed as $\chi^2(pq(q+1))$.

3. DATA AND ESTIMATION RESULTS

3.1. Data

Quarterly data on federally insured commercial bank balance sheet items (e.g. on total assets and total loans) were obtained from the Report of Condition and Income (or Call Reports). The data is available on-line from the Federal Reserve Bank of Chicago from 1976Q1 to 1999Q3. In order to construct consistent time series, we rely heavily on notes created by Kashyap and Stein (2000) to adjust for changes over time in variable definitions. A fuller discussion of the data employed and variables constructed appears in the Appendix A.

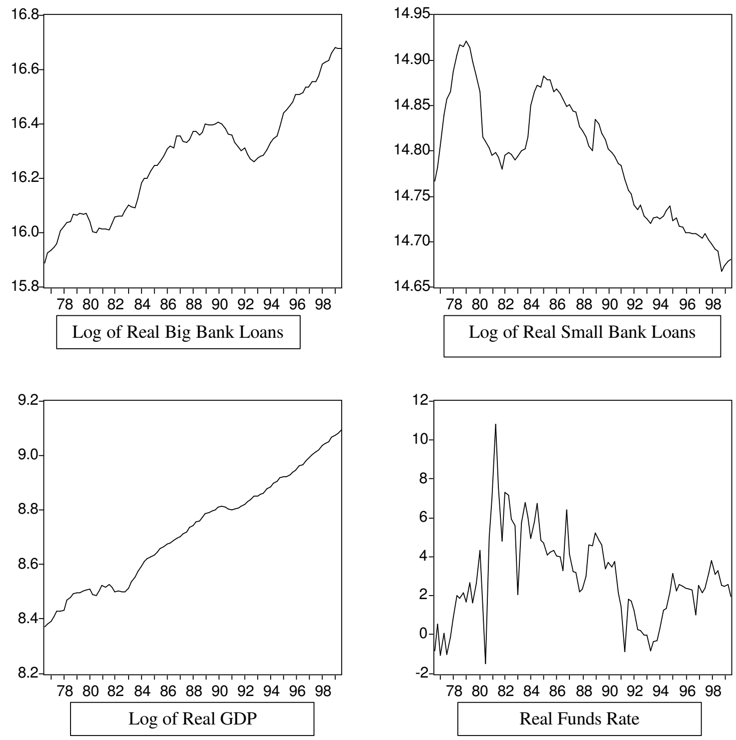
We divide the banks into two size categories, those with assets less than or equal to $300 million, and those with assets over $300 million C in 1999 dollars.[5] Banks are placed in a size category based on their real total assets for that quarter, where the real total assets are total assets deflated by the consumer price index not seasonally adjusted. Aggregated data on bank loans are deflated by the consumer price index, and then logged.[6] Most of the empirical work regarding the bank-lending channel uses the nominal federal funds rate as the measure of the indicator of the monetary policy, following Bernanke and Blinder (1992). In this paper we construct quarterly data on the real federal funds rate as an indicator of monetary policy because it more plausibly captures the real cost of borrowing, which in turn affects the real sector of the economy. Appendix B provides details of constructing the expected inflation rate, and thereby the real federal funds rate, which is defined as the difference between nominal federal funds rate and expected inflation rate. We note that our measure of expected

[5] We use these divisions since Kishan and Opiela (2000) find banks with assets <= $300 million and with capital leverage ratio <= 8% to be the most responsive. Gilbert and Hansen (2001) also use the same division.

[6] Kashyap and Stein (2000) explain how they dealt with bank mergers. Since we look at aggregates of small and big banks, we do not have the same difficulties with mergers. If a small bank (a big bank) is still classified as a small bank (a big bank) after merging with another bank, then there is no problem. But even if a small bank switches its classification from small to big after merging with another bank in a specific quarter, this bank will be switched to the big bank category after the merger, and again there is no problem.

inflation is predetermined at time t, so that a policy change in the nominal funds rate translates directly into a change in the real federal funds rate at time t. For comparison to the literature, we have also estimated a version of our model using the nominal funds rate as our measure of policy, and the results are quite similar. Finally, the log of real gross domestic product measures aggregate economic activity.

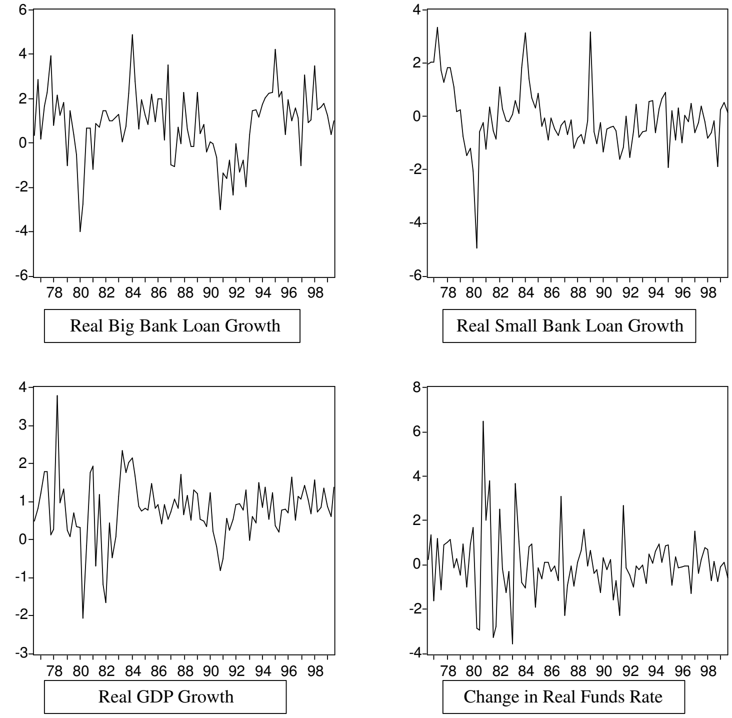
FIG. 1. Time Series in Levels



The time series in levels and in differences are shown in Figure 1 and Figure 2, respectively. On the basis of Augmented Dickey-Fuller (henceforth, ADF) tests, all variables appear to be nonstationary.[7] The Schwarz information criterion indicates that our VAR has lag length one. Because all series have unit roots, we conduct the Johansen-type likelihood ratio tests for cointegration. The results given in Table 1 indicate the existence of one cointegrating vector. Thus, our benchmark model is identified as a

[7]Before doing the ADF tests, we first tested the adequacy of the lag specification with diagnostic Q-statistics, serial correlation LM tests, and ARCH tests. All series passed these tests.

FIG. 2. Time Series in Differences



first-order linear VECM as follows:

$$DX_t = A_0^0 + A_1^0 * DX_{t-1} + A_2^0 * EC_{t-1} + E_t^0, \tag{7}$$

where $EC_t = BL_t - 2.61 * SL_t - 2.08 * Y_t - 0.03 * RFR_t + 40.52.$[8]

3.2. Estimation of the LSTVECM

Table 2 reports the results of linearity tests for each equation of the VECM and for the system as a whole. We considered a range of possible threshold variables z, listed in the first column. The tests for linearity, H_0, reject linearity in the system test for all the threshold variables we considered except DSL_{t-1}. The rejection of linearity is strongest when the

[8]Because real GDP is seasonally adjusted, we seasonally adjust the growth rate of bank loans and the expected inflation rate. In order to get consistent series when computing the error-correction term, the bank loans series in level are also seasonally adjusted.

TABLE 1.

Johansen Cointegration Tests

Sample: 1976:3-1999:3
Series in level: BL, SL, Y and RFR

Eigenvalue	Likelihood Ratio	5 Percent Critical Value	1 Percent Critical Value	Hypothesized No. of CE(s)
0.245	49.916	47.21	54.46	None *
0.177	23.779	29.68	35.65	At most 1
0.044	5.717	15.41	20.04	At most 2
0.016	1.489	3.76	6.65	At most 3

*(**) denotes rejection of the hypothesis at 5%(1%) significance level
L.R. test indicates 1 cointegrating vector at 5% significance level

Normalized Cointegrating Coefficients: 1 Cointegrating Equation
(standard errors in parentheses)

BL	SL	Y	RFR	Constant
1.000	−2.608	−2.078	−0.032	40.524
	(1.327)	(0.603)	(0.019)	

Notes: Trace statistic for a system with autoregressive order one, linear deterministic trend in the variables and in the cointegration vector(s). The critical values are from Eviews 3.1. BL, SL, Y, and RFR denote the log of the real big bank loans, real small bank loans, real GDP and the real federal funds rate, respectively.

transition variable is either the change in the policy variable ($DRFR_{t-1}$) or the change in real GDP (DY_{t-1}).

We next report results for the test H_{0a}, the test for the significance of the third order terms in the Taylor expansion on which the linearity test H_0 is based. Rejection indicates that the logistic smooth transition model would best fit the data. We only report these results for variables that led to rejection of linearity in test H_0. We reject H0a when $DRFR_{t-1}$ is the transition variable.

Finally, we report results for the test H_{0b}, the test for the significance of the second order terms in the Taylor expansion. Rejection indicates that the exponential smooth transition model would best fit the data. We only conduct this test for the variables that did not reject H_{0a}. We reject H_{0b} for DBL_{t-1} and DY_{t-1}.

Our results provide strong evidence not only against linearity but also in favor of a logistic smooth transition VECM (henceforth, LSTVECM) when the transition variable is the lagged change in the real federal funds rate ($DRFR_{t-1}$). Hence we adopt that variable as the transition variable.

There can be numerical problems in estimation of smooth transition regression models related to estimating the slope of the transition function

TABLE 2.

P-values of Linearity Tests

z_t	DBL	DSL	DY	DRFR	System
H_0					
DBL_{t-1}	0.174	0.003	0.143	0.199	0.029*
DSL_{t-1}	0.207	0.104	0.092	0.040	0.053
DY_{t-1}	0.024	0.070	0.006	0.062	0.001*
$DRFR_{t-1}$	0.707	0.714	0.007	0.000	0.005*
H_{0a}					
DBL_{t-1}	0.418	0.024	0.420	0.927	0.188
DY_{t-1}	0.038	0.361	0.011	0.566	0.057
$DRFR_{t-1}$	0.608	0.696	0.017	0.077	0.043*
H_{0b}					
DBL_{t-1}	0.031	0.008	0.272	0.081	0.007*
DY_{t-1}	0.300	0.029	0.128	0.582	0.050*

Notes: * indicates rejection of the null at the 5% significance level. DBL, DSL, DY, DRFR, and z denote real big bank loan growth, real small bank loan growth, real GDP growth, the change in the real federal funds rate, and the transition variable, respectively.

γ and the threshold value k. The problems with estimating the threshold value have been outlined in Hansen (1997), and we follow his advice to deal with these by using a grid search. There are also potential problems with the smooth transition parameter. When γ is large the smooth transition regression model is very close to a threshold regression model. This can make estimation of γ difficult in small samples, because accurate estimation requires a sufficient number of observations of the transition variable on both sides of k. We adopt a two-dimensional grid search to determine initial values for γ and k. We do this by picking values of γ and k that minimize the log of the determinant of the variance-covariance matrix of residuals. In the final step we use the prior estimates of all parameters except γ to get estimates of all the parameters including k, given the previously estimated value γ.

Our estimation results are reported in Table 3. The estimation of the smooth transition parameter γ equals 74.55. The threshold value k equals -1.69, which is significantly different from zero and lies in the lower tail of the distribution of the change in the real federal funds rate. The transition function $F(z_{t-d})$ can be written as $(1+\exp(-74.55*(DRFR_{t-1}+1.697)/1.493))^{-1}$. The histogram of the transition variable and the graph of the transition function are depicted in Figure 3.

It is important to note that in the equations for the growth rate of output (DY_t) and the change in the real federal funds rate ($DRFR_t$), the coeffi-

TABLE 3.

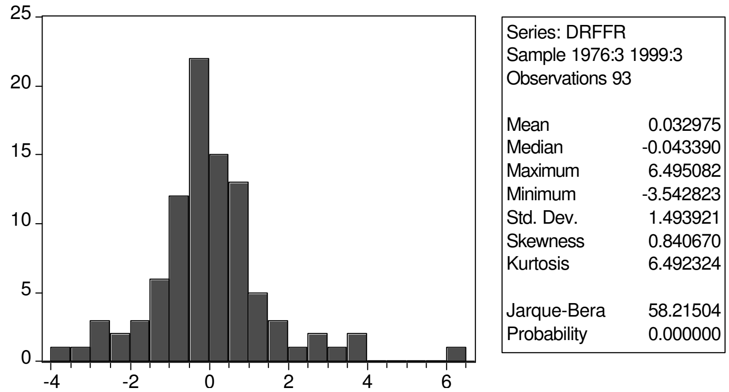
The Estimation of LSTVECM

	DBL	DSL	DY	DRFR
Constant	−1.331	1.028	4.474	11.492
	(0.697)	(0.654)	(0.014)	(0.000)
DBL_{t-1}	0.918	0.514	−0.111	−0.091
	(0.169)	(0.251)	(0.754)	(0.870)
DSL_{t-1}	−0.745	−0.016	−0.057	1.260
	(0.450)	(0.980)	(0.914)	(0.129)
DY_{t-1}	−0.088	−0.301	1.163	0.461
	(0.931)	(0.659)	(0.032)	(0.589)
$DRFR_{t-1}$	−0.446	0.473	1.924	4.345
	(0.775)	(0.652)	(0.021)	(0.001)
EC_{t-1}	−2.766	1.302	10.176	27.841
	(0.597)	(0.711)	(0.000)	(0.000)
$F(z_{t-1})$	1.637	−1.430	−3.877	−11.987
	(0.633)	(0.535)	(0.034)	(0.000)
$DBL_{t-1} * F(z_{t-1})$	−0.606	−0.324	0.194	0.067
	(0.369)	(0.475)	(0.588)	(0.906)
$DSL_{t-1} * F(z_{t-1})$	1.048	0.296	0.227	−1.336
	(0.294)	(0.660)	(0.669)	(0.112)
$DY_{t-1} * F(z_{t-1})$	0.499	0.555	−1.033	0.101
	(0.629)	(0.425)	(0.061)	(0.908)
$DRFR_{t-1} * F(z_{t-1})$	0.186	−0.588	−1.861	−4.388
	(0.905)	(0.575)	(0.026)	(0.001)
$EC_{t-1} * F(z_{t-1})$	2.186	1.696	−10.265	−26.813
	(0.683)	(0.638)	(0.000)	(0.000)
R_2	0.321	0.488	0.311	0.485

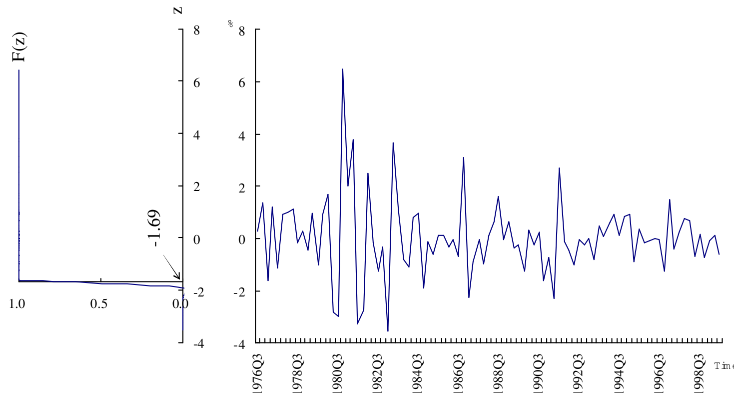
Notes: P-values are in parenthesis. DBL, DSL, DY, and DRFR, EC, z denote real big bank loan growth, real small bank loan growth, real GDP growth, a change in real federal funds rate, error-correction term and transition variables, respectively. The transition function $F(z_{t-1}) = (1 + \exp\{-74.55 * (z_{t-1} + 1.697)/1.493\}) - 1$. The error-correction term $EC_t = BL_t C 2.61 * SL_t C 2.08 * Y_t C 0.03 * RFR_t + 40.52$.

cients on their own lags are greater than one (in absolute value). This may appear to indicate that the model exhibits nonstationarity. To address this issue we examine the two extreme regimes. In one the transition function equals one, so the dynamics will be captured by the sum of the coefficients associated with their own lags. Using our estimation results, the DY_t and

FIG. 3. Transition Variable



a. Histogram of the change in the real federal funds rates



b. Transition function and time series

$DRFR_t$ equations can be expressed as:

$$\begin{aligned} DY_t &= 0.6 + 0.08 * DBL_{t-1} + 0.17 * DSL_{t-1} + 0.13 * DY_{t-1} \\ &+ 0.06 * DRFR_{t-1} - 0.09 * EC_{t-1} \\ DRFR_t &= -0.5 - 0.02 * DBL_{t-1} - 0.08 * DSL_{t-1} + 0.56 * DY_{t-1} \\ &- 0.04 * DRFR_{t-1} + 1.03 * EC_{t-1} \end{aligned}$$

The sum of the coefficients associated with DY_{t-1} equals 0.13 in equation DY_t, and that associated with $DRFR_{t-1}$ equals -0.04 in equation $DRFR_t$. Thus there is no issue of nonstationarity.

The other extreme case is when the transition function equals zero. Our estimated model can be expressed as:

$$\begin{aligned}
DY_t &= 4.47 - 0.11 * DBL_{t-1} - 0.06 * DSL_{t-1} + 1.16 * DY_{t-1} \\
&+ 1.92 * DRFR_{t-1} + 10.18 * EC_{t-1} \\
DRFR_t &= 11.49 - 0.09 * DBL_{t-1} + 1.26 * DSL_{t-1} + 0.46 * DY_{t-1} \\
&+ 4.35 * DRFR_{t-1} + 27.84 * EC_{t-1}
\end{aligned}$$

Here it appears that unstable dynamics may be brought about by the coefficient on DY_{t-1} in equation DY_t and the coefficient on $DRFR_{t-1}$ in equation $DRFR_t$, which equal 1.16 and 4.35, respectively. However, upon further reflection this may not be a concern. First, it is clear that these regions are not common in the sample. But, more importantly, we find that the coefficients associated with the error correction term are large and stabilizing. For example, consider a state of the world with $DRFR_{t-1} << -1.69$, so that the transition function is zero and the model looks to be potentially nonstationary. But a large decline in RFR_t also results in a larger (positive) value for the error correction term EC_t, which in turn tends to increase $DRFR_t$ and counter the direct effect of $DRFR_{t-1}$ on $DRFR_t$. Of course, a more formal approach is to consider the impulse response functions and make sure the model generates a stationary response to disturbances. We do this below.

One of the crucial issues we are concerned is whether the behavior of big bank loans is different from small bank loans. Our estimation results show the coefficients in the equations of bank loans are insignificantly different from zero. We conduct the log-likelihood ratio (henceforth, LR) test to see the equality of the coefficients on the first two equations in our estimation. The LR statistics equals 48.29, much greater than $\chi^2_{12,0.05}$, so we overwhelmingly reject the null of equality. This implies that large bank and small bank loans behave differently.

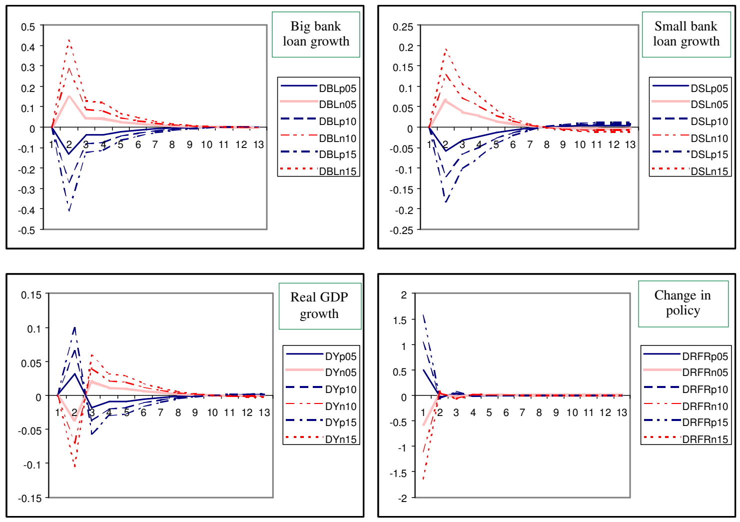
4. INVESTIGATING THE ASYMMETRIES

Based on the estimated model, we investigate the asymmetric effects which are generated as responses to shocks to monetary policy. Because nonlinear models can exhibit asymmetries with respect to both the size and sign of shocks, we calculate the generalized impulse response functions (henceforth, IRFs), following the methods described by Koop, Pesaran, and Potter (1996).[9] Because IRFs in nonlinear models are history-dependent,

[9] See the Appendix C for details of computing the generalized IRFs.

we calculate these for a contractionary period (1980Q4) and an expansionary period (1983Q1). The results are shown in Figures 4-7.

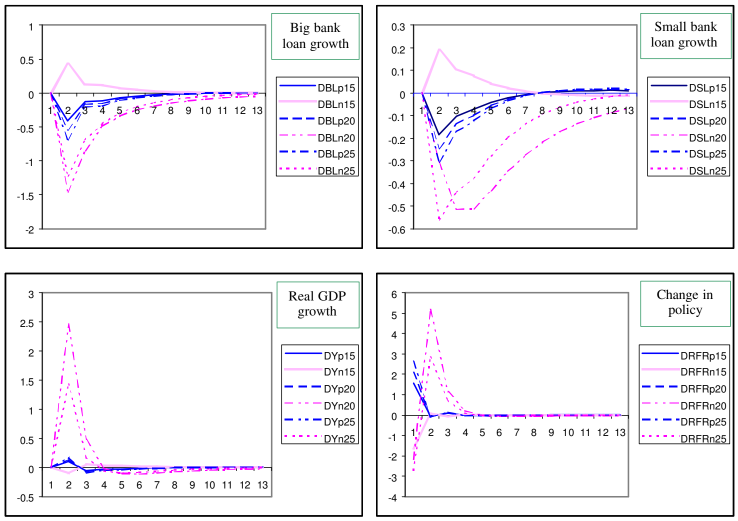
FIG. 4. Impulse Response Functions to the Relatively Small Shocks in 1980:4



The 'p' and 'n' denote the positive and negative shock, respectively. The number 05, 10, and 15 denote the different standard deviations in size. For example, DBLp05 shows the response of DBL to a positive one-half standard deviation shock.

Figure 4 shows our estimates of the impulse responses of DBL, DSL, DY, and $DRFR$ to shocks to monetary policy changes, $DRFR$, in 1980Q4. Panel (c) of Figure 4 shows that in response to a positive shock to $DRFR$, real output growth first rises sharply for one quarter, and then declines sharply. It reaches its trough about two quarters after the $DRFR$ shock, and gradually rebounds to its pre-shock level about nine quarters after the $DRFR$ shock. For a positive one standard deviation shock to the change in the real federal funds rate, real output growth rises to about 0.07 percent above baseline, then declines, reaching a trough about 0.04 percent below the baseline before gradually returning to the baseline path. In panel (a) of Figure 4, there is a short, sharp, and significant decrease in growth of real big bank loans in response to a positive shock to the $DRFR$. After this large decline, big bank lending growth declines toward the baseline, which it returns to about two and one-fourth years after the shock. We attribute the decline in lending that immediately follows a monetary contraction to the increased costs of borrowing from banks. As expected, the response of DBL, plotted in panel (a), is much greater than the response of DSL, plotted in panel (b). Because large firms have relatively greater access to alternative sources of finance, (for example they can issue corporate bonds), when large firms face a contractionary policy which may increase their costs of borrowing from banks, these large firms will choose to find other sources of finance rather than pay the higher cost of loans. This reduces the volume of loans at the big banks. Small firms do not have this ability to easily access other sources of finance. When small firms face an increased cost of borrowing due to a contractionary policy, their dependence on bank loans makes them more likely pay the higher cost. Therefore, the small banks will not have as big a change in the volume of loans. In this sense it follows that the bigger the bank, the larger the change in loan growth in response to a change in monetary policy.

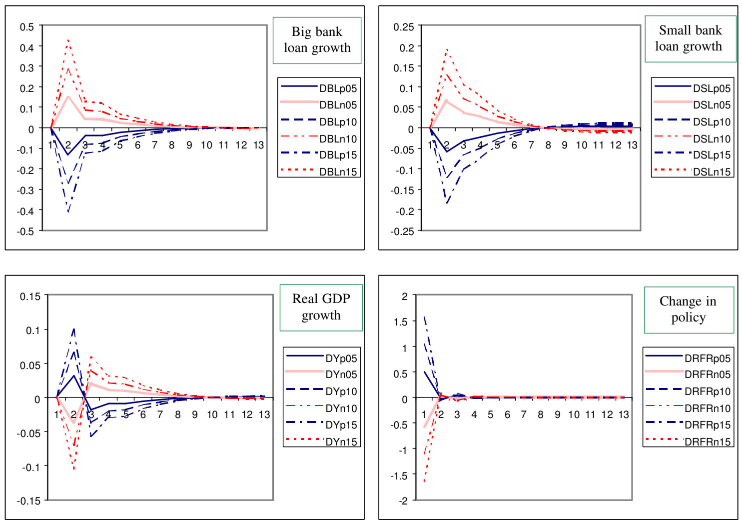
FIG. 5. Impulse Response Functions to the Relatively Big Shocks in 1980:4



The ‘p’ and ‘n’ denote the positive and negative shock, respectively. The number 15, 20, and 25 denote the different standard deviations in size. For example, DBLp15 shows the response of DBL to a positive one and one-half standard deviation shock.

Figure 5 shows the impulse response functions for large shocks to monetary policy in 1980Q4. Compared to Figure 4, we see that both positive and negative shocks cause only slightly different responses when the size of the shock is not greater than one and one-half standard deviation. However, the responses to a negative shock are completely flipped around when the size of the shock is greater than one and one-half standard deviation. This happens because such a large negative shock to the change in the real federal funds rate causes a switch from one regime to another. The large negative shock essentially decreases the transition variable so much that it declines below the threshold value of −1.7 percent, leading to a regime change and vastly different dynamics. Here a negative two and one-half standard deviation decline in the change in the real federal funds rate, about −3 percent, causes a large decline in growth of real big bank loans (−1.25 percent), in growth of real small bank loans (−0.57 percent), but a large increase in real output growth (+1.5 percent) and in the change in the real federal funds rate itself (+3 percent). These responses are temporary, with output growth and the change in the real federal funds rate declining quickly to the baseline path, while bank loan growth increasing more gradually. Small bank loan growth only returns near the baseline level after more than two years.

FIG. 6. Impulse Response Functions to the Relatively Small Shocks in 1983:1

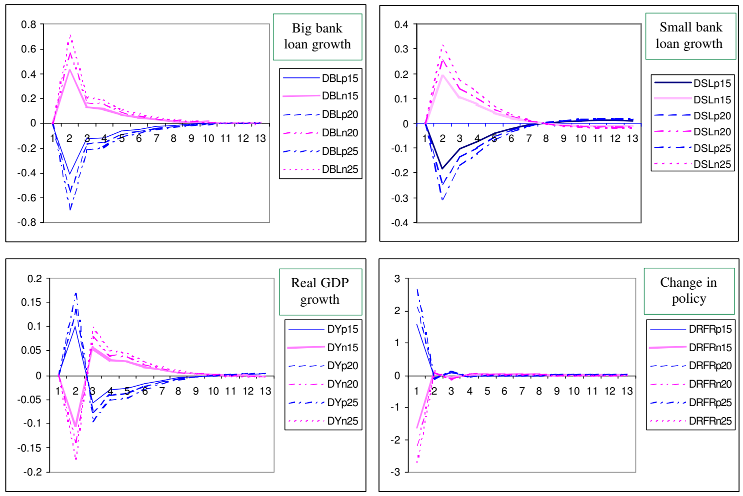


The ‘p’ and ‘n’ denote the positive and negative shock, respectively. The number 05, 10, and 15 denote the different standard deviations in size. For example, DBLp05 shows the response of DBL to a positive one-half standard deviation shock.

The impulse response functions for the model for 1983Q1 in Figures 6 and 7 do not show this remarkably different response to the different sign and size of the shock. Comparing Figure 4 to Figure 6, the responses to small shocks are very similar despite the different initial conditions. However, comparing Figure 5 to Figure 7, the responses differ greatly to shocks greater than one and one-half standard deviation.

Our results show how change in monetary policy will bring about changes in economic activity and loan growth. These results imply that bank lend-

FIG. 7. Impulse Response Functions to the Relatively Big Shocks in 1983:1



The 'p' and 'n' denote the positive and negative shock, respectively. The number 15, 20, and 25 denote the different standard deviations in size. For example, DBLp15 shows the response of DBL to a positive one and one-half standard deviation shock.

ing behavior is not independent of the monetary transmission mechanism and has different impacts due to the differences in bank size. Our results also show that the asymmetric effect of policy is not always intensified by the bank lending channel. That is, different signs of shocks and different initial conditions do not give rise to significant differences in responses when the shocks are small. When the sizes of the negative shocks are sufficiently big they cause a change in regime and thereby cause asymmetries.

5. CONCLUDING REMARKS

We employ the logistic smooth transition vector error correction model (LSTVECM) to investigate the asymmetric interaction of bank lending, aggregate output and monetary policy. We differentiate the effects of expansionary and contractionary monetary policy on loan growth and output. Our results indicate that the asymmetric effect is not intensified by the bank lending channel; however, the different sizes of the shocks to the change in the real federal funds rate lead to large asymmetries in the case of big negative shocks to the change in the real federal funds rate. Our results show that big bank loan growth has a much greater response to monetary policy, compared to that of small banks. We also provide the evidence that banks play an important role in the monetary transmission mechanism.

We imposed two strong assumptions in our model. First, we assume that each equation in our system has the same threshold value and the same smoothing parameter; therefore we have the same transition function in each equation. Second, we only assume there is a single threshold, a two-regime model. In this sense the state of the world is only described by two regimes. In future work it might be useful to allow multiple regimes as well as multiple thresholds.

APPENDIX: DATA DESCRIPTION

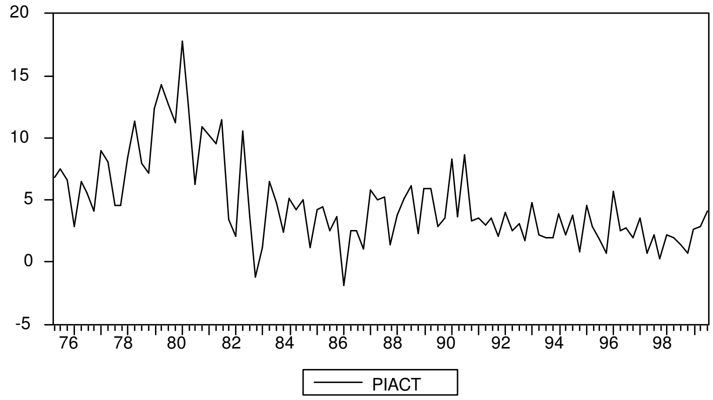
Our sample is drawn from the set of all insured commercial banks whose regulatory filings show that they have positive assets. Between the first quarter of 1976 and the third quarter of 1999, this yields 1,000,524 bank-quarters of data. We construct two main series from the Call Reports that are used in our empirical work. Our size categories are formed by sorting the banks on the basis of their real total assets. Real total assets are from the call report item rcfd2170, deflated by the consumer price index. Throughout our sample, the total assets data are measured on a consistent basis, but much more detail concerning bank assets and liabilities was collected starting in March 1984. Therefore many series are defined somewhat differently before and after that date.

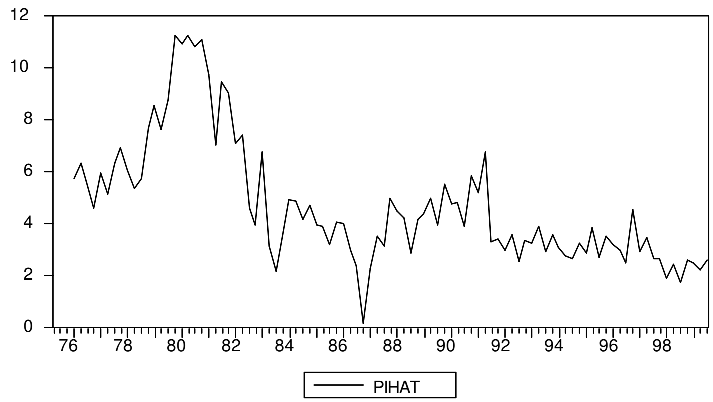
The data for total loans after March of 1984 come from item rcfd1400 in the Call Reports. The series is defined as “Gross Total Loans and Leases”. In March of 1984, the series was changed to include “Lease Financing Receivables”, which comes from item rcfd2165 in Call Reports. Therefore, prior to March 1984, the series rcfd1400 and the series rcfd2165 must be summed to insure comparability. As mentioned by Kashyap and Stein (2000), we unfortunately have no way to avoid some discontinuity for many big-bank loans, because in December 1978 banks began reporting their lending on a consolidated basis with foreign and domestic loans no longer separately identified.

APPENDIX: CONSTRUCTING THE REAL FEDERAL FUNDS RATE

The BLS releases the consumer price index (CPI) for the previous month on the 15th of each month. For example, we know the CPI for December 2001 on the 16th of January 2002. Therefore, during the 1st-15th of January 2002, we only know the CPI prior to December 2001. We then can compute the monthly inflation rate for November 2001 and prior to that time. Because the quarterly inflation rate can be calculated by the formula $(CPI_t/CPI_{t-3} - 1) * 100$, we also know the quarterly inflation rate for the third quarter of 2001 during that time. Thus, during the 1st-15th of January 2002, we can forecast the quarterly inflation rate for the second quarter of 2002 using not only the quarterly inflation rate for the third quarter of 2001, but also the monthly inflation rate for November 2001 and October 2001.

From the 16th of January 2002 to the 15th of February 2002, we can compute the monthly inflation rate for December 2001 and prior to that time. We then can forecast the quarterly inflation rate for the second quarter of 2002 using the quarterly inflation rate for the third quarter of 2001, the monthly inflation rate for December 2001, November 2001, and October 2001. From the 16th of February 2002 to the 15th of March 2002, we can compute the monthly inflation rate for January 2002. Then, we can forecast the quarterly inflation rate for the second quarter of 2002 using the quarterly inflation rate for the third quarter of 2001, the monthly inflation rate for January 2002, December 2001, November 2001, and October 2001. From the 16th to the last day of March 2002, we can compute the monthly inflation rate for February 2002. During that time, we can forecast the quarterly inflation rate for the second quarter of 2002 using the quarterly inflation rate for the third quarter of 2001, the monthly inflation rate for February 2002, January 2002, December 2001, November 2001, and October 2001. The resulting quarterly inflation rate forecasting for second quarter of 2002 can be obtained by weighting over these four types of forecasting and are presented in annualized rate. Throughout our analysis we use the (monthly) CPI over the period 1975:02-1999:03 to estimate the quarterly expected inflation rate over the period 1976:1-1999:3. In the graph below, the inflation rate from the actual data is called PIACT, while our constructed inflation rate forecasting is called PIHAT.





To demonstrate the PIHAT performed well, we conduct some diagnostic tests, including the test of unbiasedness and efficiency, the Breusch-Godfrey Serial Correlation LM Test, ARCH Test, and forecast-encompassing test.

One widely used test for biasedness regresses the actual values PIACT on a constant and the forecast values PIHAT:

$$PIACT = a + b * PIHAT + e,$$

and tests whether $a = 0$ and $b = 1$. Table B.1 reports the results for the current quarter forecast of inflation rate. It indicates no problem of bias, with an insignificant constant and a significant coefficient on the forecast. The Wald test indicates that we cannot reject the joint test of $a = 0$ and $b = 1$. Table B.2 and Table B.3 show that the null hypothesis of no serial correlation is not rejected at even the 10% significant levels. That is, the serial correlation tests indicate no evidence of serial correlation. Thus, our forecast appears unbiased and efficient.

TABLE 1.

Test of Unbiasedness

PIACT	Coefficient	Std. Error	t-Statistic	Prob.
C	−0.217	0.585	−0.370 0.712	
PIHAT	1.046	0.111	9.414	0.000
Wald Test under H_0: $a = 0$ and $b = 1$				
F-statistic	0.086		Probability	0.918
Chi-square	0.172		Probability	0.918

TABLE 2.

Breusch-Godfrey Serial Correlation LM Test:

F-statistic	0.878	Probability	0.419
Obs*R-squared	1.799	Probability	0.407

TABLE 3.

ARCH Test

F-statistic	1.432	Probability	0.235
Obs*R-squared	1.440	Probability	0.230

For forecast-encompassing test, we follow the procedure applied by Jansen and Kishan (1996). First, we regress PIACT on a constant and $PIACT(-3)$ to get the fitted value, PIACTF. Then we regress PIACT on a constant, PIACTF and PIHAT to test whether PIHAT adds information to the forecast PIACTF. PIHAT seems to have more information than PIACTF but we are not sure which one is a better forecast for the inflation rate. The encompassing test mainly provides evidence to compare the different information content of the variables. In our application, the test asks whether, given the conventional forecast (PIACTF), our constructed forecast (PIHAT) adds any useful information for forecasting. Similarly, we can ask whether, given our constructed forecast, the conventional forecast adds any useful information for forecasting. To conduct this test, Jansen and Kishan (1996) suggest running two regressions. One is to regress the difference between PIACT and PIHAT on the difference between PIACTF and PIHAT. The other is to regress the difference between PIACT and PIACTF on the difference between PIHAT and PIACTF. The results of the encompassing tests are reported in Table B.4. For the current quarter inflation rate forecast, our constructed forecast (PIHAT) encompasses the conventional forecast (PIACTF) at the 5% significant level (t-statistic 4.41, probability value 0.00), while the conventional forecast (PIACTF) does not encompass our constructed forecast (PIHAT) at the 5% significant level (t-statistic −1.18, probability value 0.24). Thus our constructed forecast (PIHAT) contains information not available in the conventional forecast (PIACTF), and is in this sense superior to PIACTF. Consequently, we demonstrate the evidence that our constructed forecast (PIHAT) passes the diagnostic tests of unbiasedness and efficiency and encompassing test, and that there is no serial correlation.

TABLE 4.

Forecast-Encompassing Tests

$PIA = PIACT - PIHAT$

$PIAR = PIACTF - PIHAT$

Dependent Variable: PIA

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PIAR	−0.366	0.310	−1.183	0.240

$PIB = PIACT - PIACTF$

$PIBR = PIHAT - PIACTF$

Dependent Variable: PIB

Variable	Coefficient	Std. Error	t-Statistic	Prob.
PIBR	1.367	0.310	4.411	0.000

APPENDIX: COMPUTING THE GENERALIZED IMPULSE RESPONSE FUNCTIONS FOR LSTVECM

The following algorithm is used to compute the generalized impulse responses in this paper. The nonlinear model generating the q-dimensional variable in difference DX is assumed to be known, that is, sampling variability is ignored. Because we have error-correction term, we need convert the variable in difference to the variable in level. Then we can compute the evolution of the error-correction term. The shock to the ith variable of DX, v_{i0}, occurs in period 0, and responses are computed for h periods thereafter. The shock is a positive or negative 0.5, 1, 1.5, 2, or 2.5 standard deviation shock to the DRFR. With the DRFR placed last in the ordering, there is no contemporaneous effect on other variables in the system. The structural shocks are identified using a Choleski decomposition in that order.

1. Pick a history ω_{t-1}^r. The history is the actual value of the lagged variables at a particular date.

2. Pick a sequence of (q-dimensional) shocks $v^b_{t+n}, n = 0, \ldots, h$. The shocks are drawn with replacement from the estimated residuals of our LSTVECM. The shocks are assumed to be jointly distributed, so if date t's shock is drawn, all q residuals for date t are collected.

3. Using ω^r_{t-1} and v^b_{t+n}, compute the evolution of DX_{t+n}, over $(h+1)$ periods. Then calculate the evolution of the variables in levels $X_{t+n} = DX_{t+n}/100 + X_t$ over h periods. Therefore, the error correction term $EC_{t+n} = (1, -2.61, -2.08, -0.03) * X'_{t+n} + 40.52$ over h periods. Denote the resulting baseline path in differences $DX_{t+n}(\omega^r_{t-1}, v^b_{t+n}), n = 0, \ldots, h$.

4. Substitute v_{i0} for the $i, 0$ element of v^b_{t+n} and compute the evolution of DX_{t+n} over $(h+1)$ periods. Then calculate the evolution of the variables in levels $X_{t+n} = DX_{t+n}/100 + X_t$ over h periods. Therefore, the error correction term $EC_{t+n} = (1, -2.61, -2.08, -0.03) * X'_{t+n} + 40.52$ over h periods. Denote the resulting simulated path $DX_{t+n}(v_{i0}, \omega^r_{t-1}, v^b_{t+n}), n = 0, \ldots, h$.

5. Repeat steps 2 to 4 for 10,000 times and compute $G^a_{t+n}(v_{i0}) = [DX_{t+n}(v_{i0}, \omega^r_{t-1}, v^b_{t+n}) - DX_{t+n}(\omega^r_{t-1}, v^b_{t+n})]/10000$ for the averaged impuse response functions.

Notice that, at Step 1, dates are chosen from a particular subsample of the data, we try those dates for which lagged DRFR was maximum and minimum. In the sense that monetary policy is extremely contractionary and extremely expansionary at that moment, which is 1980Q4 and 1983Q1, respectively.

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