Economic Review

Federal Reserve Bank of San Francisco

1992 Number 3

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The Federal Reserve Bank of San Francisco's Economic Review is published quarterly by the Bank's Research Department under the supervision of Jack H. Beebe, Senior Vice President and Director of Research. The publication is edited by Judith Goff. Design, production, and distribution are handled by the Public Information Department, with the assistance of Karen Flamme and William Rosenthal.

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Printed on recycled paper with soybean inks.

Controlling Inflation with an Interest Rate Instrument

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They would like to thank Evan Koenig, Bennett McCallum, Ronald Schmidt, Bharat Trehan, Adrian Throop, Carl Walsh and participants in the Conference on Operating Procedures at the Federal Reserve Bank of St. Louis, June 18-19, 1992 for helpful comments on an earlier draft, Andrew Biehl for his efficiency and diligence in computing the many regressions and simulations in this paper, and Erika Dyquisto for preparing the document.

In this paper we examine the effectiveness in controlling long-run inflation of feedback rules for monetary policy that link changes in a short-term interest rate to an intermediate target for either nominal GDP or M2. We conclude that a rule aimed at controlling the growth rate of nominal GDP with an interest rate instrument could be an improvement over a purely discretionary policy. Our results suggest that the rule could provide better long-run control of inflation without increasing the volatility of real GDP or interest rates. Moreover, such a rule could assist policymakers even if it were used only as an important source of information to guide a discretionary approach.

In Congressional testimony, Chairman Greenspan and other Federal Reserve officials have made it clear that price stability is the long-run goal of U.S. monetary policy.[1] At the same time, reducing fluctuations in real economic activity and employment remains an important short-term goal of the System. However, the desire to mitigate short-term downturns inevitably raises the issue of whether this goal should take precedence over price stability at any particular point in time. At present, the Federal Open Market Committee (FOMC) resolves this issue on a case by case basis, using its discretion to set policy after analysis of a wide array of real and financial indicators covering the domestic and international economies.

Economic theory suggests that monetary policy tends to have an inflationary bias under such a discretionary system. This bias can be eliminated by the monetary authority pre-committing itself to a policy rule that would ensure price stability in the long run (Barro 1986). Even if the monetary authority is not willing to adhere rigidly to a rule, a discretionary approach could benefit from the information provided by a properly designed rule. For example, the instrument settings defined by the rule at any time could be regarded as the baseline policy alternative that would serve as the starting point for policy discussions. At its discretion, the FOMC could select a policy that was easier, tighter or about the same as that called for by the policy rule. Under such an approach, the rule could provide information that would help to guide short-run policy decisions toward those consistent with the long-run goal of price stability.

In this paper, we assess the effectiveness of so-called nominal feedback rules of the type suggested by Bennett McCallum (1988a, 1988b). These rules specify how a policy instrument (a variable that is under the direct control of the central bank) responds to deviations of an intermediate target variable from pre-established values. Earlier work (Judd and Motley 1991) suggests that a rule in which the monetary base is used as the instrument and nominal

*An earlier version of this paper (Judd and Motley 1992) will be published under the same title in a forthcoming issue of *Finance and Economics Discussion Series,* Board of Governors of the Federal Reserve System.

[1]See Greenspan (1989) and Parry (1990).

GDP is used as the intermediate target could have produced price level stability with a high degree of certainty over the past 30 years.

Over many years, the Fed has shown a strong preference for conducting policy using an interest rate instrument, as opposed to a reserves or monetary base instrument. In the present paper, we examine rules that use an interest rate instrument in conjunction with nominal GDP as the intermediate target. In addition, since the mid-1980s, the Fed has used a broad monetary aggregate, M2, as its main intermediate target or indicator. Hence, we also assess the usefulness of a rule that combines an interest rate instrument with M2 as the intermediate target variable.

Evaluating the effects of policy rules in advance of actually using them is an inherently perilous task. First, the effects of a rule will depend on the structure of the economy, including several features—such as the degree of price flexibility and the way in which expectations are formed—that remain subjects of debate and disagreement among macroeconomists (Mankiw 1990). This lack of consensus about issues that crucially affect the working of the economy means that, in order to be credible, any proposed rule must be demonstrated to work well within more than one theoretical paradigm. Second, implementation of a rule could alter key behavioral parameters affecting price setting and expectations formation. This means that history may not be a good guide in evaluating rules that were not implemented in the past, and that the robustness of empirical results to alternative parameter values also must be examined.

In order to assess their effectiveness under alternative macroeconomic paradigms, we conduct simulations of two different macroeconomic models (a Keynesian model and an atheoretic vector autoregression or error correction system) that have significant followings among macroeconomists.[2] To assess the risks of adopting different rules, we examine the dynamic stability of these models under alternative versions of the rules. In addition, we use stochastic simulations to determine the range of outcomes for prices, real GDP and a short-term interest rate that we could expect if these rules were implemented and the economy experienced shocks similar in magnitude to those in the past. Finally, to test for robustness, we re-examine all of the results under plausible alternative values for key estimated parameters in the models.

[2]Our earlier paper (Judd and Motley 1991), in which the policy instrument was the monetary base, also examined the effects of a rule within the context of a very simple real business cycle (RBC) model. However, with an interest rate instrument, the price level cannot be determined in the context of that RBC model (see McCallum 1988b, pp. 61-66). Thus we did not use the RBC model in this paper.

Using these simulations we evaluate the effectiveness of the rules at controlling the price level. We also examine the effect of the rules on the volatility of real GDP and a short-term interest rate. Although we find that interest rate rules could have held long-run inflation below levels that were observed historically, they do not perform as well as base-oriented rules. However, there are reasons to believe that the base would be a less effective instrument in the future than it would have been in the past. Moreover, one simple form of the interest rate rule does appear to offer an improvement over a purely discretionary approach. Finally, we suggest a way to use a feedback rule with an interest rate instrument as an important source of information that could contribute to the effectiveness of a discretionary policy.

The remainder of the paper is organized as follows. Section I presents a brief overview of the theoretical advantages and disadvantages of alternative targets and instruments. Section II discusses the nominal feedback rules to be tested. In Section III, we present the empirical results. The conclusions we draw from this work are presented in Section IV.

I. Conceptual Issues

In this section, we discuss briefly the basic conceptual issues determining the effectiveness of alternative intermediate targets and instruments of monetary policy. To illustrate certain basic ideas, we introduce a generic form of the feedback rule that links the *instrument* variable with the *intermediate target* variable. This generic feedback rule may be written in the form:

$$\Delta I_t = \psi + \lambda[Z^*_{t-1} - Z_{t-1}].$$

The variable I represents the policy instrument, which is a variable under the direct control of the monetary authority. Z represents the intermediate target variable of policy. The rule specifies that the change in the policy instrument should be equal to the change desired in steady-state equilibrium, ψ, plus an adjustment term, $\lambda[Z^*_{t-1} - Z_{t-1}]$. This latter term describes the monetary authority's response to deviations between the actual level of the intermediate target variable (Z) and its desired level (Z^*). The strength of the monetary authority's response to such deviations is defined by λ. Thus, the rule permits policy to incorporate varying degrees of aggressiveness in pursuing the intermediate target.

The policy instrument, I, responds only to lagged, and hence *observed*, values of the intermediate target Z. Hence, the rule can be implemented without reference to any particular model. This is an advantage in view of the current disagreement about the "correct" model of the economy.

Nominal feedback rules may gain wider appeal because it may be possible to agree about the effectiveness of a particular rule, while disagreeing about certain aspects of how the economy actually works.

Alternative Intermediate Targets

The appeal of nominal GDP as an intermediate target lies in the apparent simplicity of its relationship with the price level, which is the ultimate long-term goal variable of monetary policy (Hall 1983). As shown by the following identity, the price level (p) is equal to the difference between nominal GDP (x) and real GDP (y), where all variables are in logarithms:

$$p = x - y.$$

This identity means that there will be a predictable long-term relationship between nominal GDP and the price level as long as the level of steady state real GDP is predictable.

According to some economists, the level of real GDP has a long-run trend, called potential GDP, which is determined by slowly evolving long-run supply conditions in the economy, including trends in the labor force and productivity (Evans 1989). To the extent that this view is correct, it is straightforward to calculate the path of nominal GDP required to achieve long-run price stability.

However, other research suggests that real GDP does not follow a predictable long-run trend, and is stationary only in differences (King, Plosser, Stock and Watson 1991). If this were the case and nominal GDP were to grow at a constant rate under a rule, the price level would evolve as a random walk, and thus could drift over time. Unfortunately, statistical tests are not capable of distinguishing reliably between random walks and trend stationary processes with autoregressive roots close to unity (Rudebusch 1993). This uncertainty over the long-run behavior of real GDP means that there is corresponding uncertainty over how the price level would behave under a nominal GDP target.[3]

Another potential problem is that the lags from policy actions to nominal GDP are relatively long, and thus targeting nominal GDP might induce instrument instability. Shorter lags tend to exist between policy actions and monetary aggregates. Hence, using an aggregate as an intermediate target could reduce the likelihood of producing instrument instability compared to a nominal GDP target.

Since the velocity of M1 began to shift unpredictably in the early 1980s, M2 has been the main intermediate target used by the Fed and so is a prime candidate for use in a feedback rule. M2 also has been identified as a potential intermediate target because its velocity (in levels) has been stationary over the past three decades (Miller 1991, Hallman, Porter and Small 1991). Its short-run relationship with spending, however, has not been very reliable. These problems have intensified in recent years, with accumulating evidence of instability in M2 velocity in 1990–1992 (Judd and Trehan 1992, Furlong and Judd 1991). Nonetheless, it may be possible to exploit its long-run relationship with prices to achieve price stability.

For present purposes, the important implication of the preceding discussion is that the choice of an intermediate target variable cannot be determined from theory alone. This choice depends on empirical factors such as the time series properties of real GDP, the degree of flexibility of prices, and the predictability of the velocity of money. Clearly an empirical investigation is needed.

Alternative Instruments

Instruments of monetary policy fall into two basic categories: aggregates that are components of the Federal Reserve's balance sheet, such as the monetary base or the stock of bank reserves, and short-term interest rates, such as the federal funds rate. Either category qualifies as a potential instrument since either can be controlled precisely in the short run by the central bank and each is causally linked to output and prices.

The monetary base has the advantage that, in principle, it is the variable that determines the aggregate level of prices, and thus would appear to be a natural instrument to use in a rule designed to achieve price stability. However, it has a number of potential disadvantages. First, using the base as an instrument could cause interest rates to become excessively volatile, and thereby impair the efficiency of financial markets. Second, the base is made up mainly of currency in the hands of the public (currently, about 85 percent), and concern for efficiency in the payments system argues for supplying all the currency the public demands. This means that controlling the base requires operating on a small component of it (bank reserves). Hence, relatively small changes in the base might require

[3]In part because of this concern, a number of authors have argued that the Federal Reserve should target prices directly (Barro 1986, and Meltzer 1984). No matter what time series properties real GDP displays, direct price level targeting obviously could avoid long-term price-level drift. The major disadvantage of price level targeting is that in sticky price models, the feedback between changes in the instrument and the price level is very long (and, in fact, longer than for nominal GDP). Thus, attempts by monetary policy to achieve a predetermined path for prices are liable to involve instrument instability (i.e., explosive paths for the policy instrument) and undesirably sharp movements in real GDP. Our earlier empirical results (Judd and Motley 1991) confirm this conjecture.

large proportional changes in reserves, which could disrupt the reserves market. Third, along with M1, the demand for the base has become relatively unstable in the 1980s compared with prior decades. The deregulation of deposit interest rates and increased foreign demand for U.S. currency apparently have induced permanent level shifts in the demand for the base, and possibly a change in its steady-state growth rate.

In Judd and Motley (1992, Appendix C) we examine the stability of the demand for base money and the issue of whether the need to supply currency on demand would seriously inhibit the use of the base as a policy instrument. We conclude that although these problems are legitimate reasons for concern whether a base rule would work well, they probably are not fatal. Nonetheless, it is worthwhile to explore the possibility of using a short-term interest rate as the instrument in the context of the feedback rule since the FOMC has shown a preference over the years for using the federal funds rate as its instrument.[4] This is our main purpose in this paper.

It is well-known that an interest rate would not be a satisfactory intermediate target for policy. The economy would be dynamically unstable in the long run (i.e., the price level would be indeterminate) if nominal interest rates were held steady at a particular level and not permitted to vary flexibly in response to shocks. However, this argument does not rule out its use as an *instrument*. If interest rate movements are linked to changes in a nominal variable (such as nominal GDP, a monetary aggregate, or the price level itself) through a rule, the price level may be determinate (McCallum 1981). Thus the question of whether an interest rate instrument would function effectively within a feedback rule cannot be answered by theory alone. Empirical work is required.

II. Nominal Feedback Rules

We examine two rules in which the interest rate is used as the instrument and one that uses the monetary base. We use the following symbols throughout: b = log of the monetary base, R = the three-month Treasury bill rate, $m2$ = log of the broad monetary aggregate, M2, x = log of nominal GDP, y^f = log of full-employment real GDP, and "*" denotes a value desired by the central bank.

Equation 1 employs nominal GDP as the intermediate target and the interest rate as the instrument.

[4]Apparently, this preference is based in part on the view that this approach avoids imparting unnecessary volatility to financial markets that would arise if policy were conducted using a reserves or monetary base instrument.

$$(1)\quad \Delta R_t = -\lambda_1[x^*_{t-1} - x_{t-1}] + \lambda_2[x^*_{t-2} - x_{t-2}]$$
$$= -\alpha[x^*_{t-1} - x_{t-1}] - \beta[\Delta x^*_{t-1} - \Delta x_{t-1}]$$

where $\alpha = (\lambda_1 - \lambda_2)$, $\beta = \lambda_2$.

Equation 2 is similar but uses M2 as the target.

$$(2)\quad \Delta R_t = -\alpha[x^*_{t-1} - \bar{V2}_{t-1} - m2_{t-1}] - \beta[\Delta x^*_{t-1} - \Delta\bar{V2}_{t-1} - \Delta m2_{t-1}],$$

where $\bar{V2}_t = \sum_{i=0}^{15}(x_{t-i} - m2_{t-i})/16$.

In order to provide a standard of comparison, we also examine a rule in which a base instrument is used to reach a nominal income target.[5]

$$(3)\quad \Delta b_t = [\Delta y^f_t + \Delta p^*_t] - \Delta\bar{VB}_t + \alpha[x^*_{t-1} - x_{t-1}] + \beta[\Delta x^*_{t-1} - \Delta x_{t-1}],$$

where $\Delta\bar{VB}_t = [(x_{t-1} - b_{t-1}) - (x_{t-17} - b_{t-17})]/16$.

The left hand sides of these equations represent the change in the policy instrument, either the annualized growth rate of the monetary base or the percentage point change in the short-term interest rate. Since in steady state the rate of interest is constant, the left hand sides of (1) and (2) are zero in equilibrium. Hence, the interest rate rules contain only a feedback component, which specifies how the interest rate is adjusted when the target variable (nominal GDP or M2) diverges from the path (in levels or growth rates) desired in the previous quarter. In (2), the target level of M2 (in logarithms) is defined as the target level of nominal income less the average level of M2 velocity over the past 16 quarters. The terms α and β define the proportions of a target "miss" (in levels and growth rates, respectively) to which the central bank chooses to respond in each quarter. In equilibrium, there are no misses and hence the interest rate is constant.

The monetary base rule is more complicated. The first

[5]In our earlier paper (Judd and Motley 1991), we also tested the following two rules:

$$\Delta b_t = \left[\Delta y^f_t + \Delta p^*_t\right] - \Delta\bar{VB}_t + \alpha\left[p^*_{t-1} - p_{t-1}\right]$$

$$\Delta b_t = \left[\Delta y^f_t + \Delta p^*_t\right] - \Delta\bar{VB}_t + \alpha\left[(y^f_{t-1} - y_{t-1}) + (\Delta p^*_{t-1} - \Delta p_{t-1})\right].$$

The price level target produced instability in the Keynesian model, while the second rule, suggested by Taylor (1985), produced dynamic instability in the vector autoregression.

term on the right-hand side of (3) represents the growth rate of nominal GDP that the central bank wishes to accommodate in the long-run, which is equal to the sum of the desired inflation rate (Δp^*) and the steady-state growth rate of real GDP (Δy^f). The second term, $\Delta \overline{VB}$, subtracts the growth rate of base velocity over the previous four years, and is designed to capture long-run trends in the relation of base growth to nominal GDP growth.[6] The third term specifies the feedback rule determining how growth in the base is adjusted when there is a target miss in the previous quarter. In steady state, this feedback term drops out, so that the rule simply states that $\Delta b_t = \Delta y_t^f + \Delta p_t^* - \Delta \overline{VB}_t$.

In all three rules, we use two lags on the levels of the intermediate target variables. As shown in (1), this specification is equivalent to including one lag on the level and one lag on the growth rate of the target variable (McCallum, 1988b). Thus the instrument is subject to both "proportional" (response to levels) and "derivative" (response to growth rates) feedback. The addition of derivative feedback can improve the performance of proportional feedback rules in some circumstances (Phillips 1954). In any event, we evaluate the performance of the rules under all three possible categories of control: proportional only ($\alpha>0, \beta=0$), derivative only ($\alpha=0, \beta>0$), and both proportional and derivative ($\alpha>0, \beta>0$).

III. Empirical Results

For each of the rules tested, we performed a number of dynamic simulations within the context of two types of model: a simple structural model based on Keynesian theory, and a theoretically agnostic vector autoregression or error correction model.

The models are described in detail in Appendix A. The Keynesian model embodies four equations, each representing a basic building block of this framework. First, there is an aggregate demand equation, relating growth in real GDP to growth in real M2 balances (or the monetary base). Second, there is a Phillips-curve equation, relating inflation to the GDP "gap" (i.e., the difference between real GDP and an estimate of its full employment level), and a distributed lag of past inflation. This latter variable reflects the basic Keynesian view that prices are "sticky," and means that there are long lags from policy actions to price changes. Third, full-employment real GDP (in levels) is assumed to have a deterministic trend. Thus the supply of real GDP in levels is unaffected by business cycle developments. Finally, the model includes an equation defining the demand for (real) money (or the monetary base) as a function of real GDP, and the nominal interest rate.

To simulate this model with a base instrument, this last equation is replaced by the equation describing the policy rule (3). In simulations with an interest rate instrument, (1) and (2), the policy rule determines the interest rate, which feeds into the M2 or base demand equation to determine the monetary aggregate. Under both instruments, the simulation model includes the aggregate demand and supply equations and the Phillips curve to determine y, y^f and p.

In addition to the Keynesian model, we also use either a vector autoregression (VAR) or a vector error correction (VECM) framework. To simulate the effects of a rule with a base instrument, we use a four-variable VAR system, including real GDP, the GDP deflator, the monetary base, and the three-month Treasury bill rate. In these simulations, the estimated equation for the base is replaced by the policy rule (3). For the interest rate rules, we use a somewhat different system of equations. Since the second interest rate rule (2) involves M2 as the intermediate target, we replace the base with M2 in the above list of variables. We use this same system to simulate the effects of (1), which uses nominal GDP as the intermediate target. In simulating the interest rate rules, the estimated interest rate equation is replaced by the appropriate policy rule.

In estimating these systems, we used standard statistical techniques as described in Appendix A to test for stationarity, cointegration, and lag length. In the system that includes M2, we found one cointegrating relationship, which we interpret as an M2 demand function. This cointegrating vector was imposed in estimating the resulting VECM. No cointegrating vector was found in the system that includes the monetary base, and hence this system was estimated as a VAR.

The simulation results fall into three categories. First, we examine the dynamic stability of each macroeconomic model when the rules are used to define monetary policy. For a policy rule to be considered, it must produce a model that has sensible steady state properties. In the long run, a feedback rule will make the price level follow the desired path, as long as it does not make the economy dynamically unstable and induce explosive paths for the endogenous variables. Given the uncertainty about the true structure of the economy, a rule must produce dynamic stability in both types of models examined, and with a range of alternative values of α and β, in order to be considered reliable. We conduct numerous simulations to see if the rules meet this test.

Second, we conduct repeated stochastic counterfactual simulations of the alternative models and rules over the

[6]The 16-quarter average was designed to be long enough to avoid dependence on cyclical conditions. As a consequence, the term can take account of possible changes in velocity resulting from regulatory and technological sources.

1960–1989 sample period to see how the principal macroeconomic variables might have evolved if the rules had been followed. In these simulations, we assume that the shocks in each equation have the same variance as the estimation errors. This procedure allows us to construct probability distributions of alternative outcomes for each rule and each model, and to calculate (95 percent) confidence intervals for long-run inflation rates as well as for short-run real GDP growth rates and for interest rate changes. This enables us to compare different rules in terms of the full range of alternative outcomes that each might produce. To compare the simulated results under the rules with the results of the policies actually pursued, we report the means and 95 percent confidence bands of the actual data over 1960–1989.

Third, we tested the robustness of these results by repeating many of the above simulations under alternative values of key parameters in our estimated models.

Dynamic Stability

The results of our analysis of the dynamic stability of the models under the various rules are shown in Table 1. To detect whether a particular combination of model, rule, and pair of α and β was dynamically stable, we computed a nonstochastic simulation covering 300 quarters. The size of the simulation's last cycle for the price level (peak-to-trough change) was divided by the size of its first cycle to form a ratio that we call s. If s is greater than 1.0, the simulation is unstable since the swings in the endogenous variable become larger as time passes, while a value of s less than 1.0 shows dynamic stability.[7] For each combination of model and rule, we performed a grid search over various combinations of α (to measure proportional control) and β (to measure derivative control). The grid extended from $\alpha = \beta = 0.0$ to $\alpha = 0.8$ and $\beta = 1.1$ (in units of 0.1 for both α and β). Excluding the combination in which $\alpha = \beta = 0.0$, which represents the no-rule case, each grid search generated 107 values of s. Although the exact specification of these searches is somewhat arbitrary, they do appear to present an accurate picture of the stability properties being investigated.

Table 1 provides a count of stable simulations for each rule under each model. As shown, the nominal GDP/base rule is dynamically stable in every simulation for both models. Thus the conclusion that an economy guided by a nominal GDP/base rule would have desirable steady state properties is quite robust across models and choices of α and β. In fact, in the case of a base instrument, the simple approach of proportional control (only) would seem to

[7]Nearly all of the simulations we observed exhibited cycles. However, the method used for detecting dynamic instability also works for simulations that do not exhibit cycles.

Table 1
Dynamically Stable Simulations by Type of Control

Rule Intermediate Target/Instrument	Proportional Only (10 trials)	Proportional and Derivative (89 trials)	Derivative Only (8 trials)	Total (107 trials)
Nominal GDP/Interest Rate				
Keynesian Model	6	68	7	81
VECM	1	13	7	21
M2/Interest Rate				
Keynesian Model	8	82	8	98
VECM	0	11	8	19
Nominal GDP/Monetary Base				
Keynesian Model	10	89	8	107
VAR	10	89	8	107

Note: The number of trials is the total number of pairs of α and β for each combination of rule and model.

Proportional Only: $\alpha > 0; \beta = 0$
Proportional and Derivative: $\alpha > 0; \beta > 0$
Derivative Only: $\alpha = 0; \beta > 0$

make sense. In any event, the risk of inducing unstable cycles by using this rule appears to be small.

The same cannot be said for the interest rate instrument, using either nominal GDP or M2 as the intermediate target. Under the vector error correction model, the rule produces only 21 stable cases out of 107 trials when nominal GDP is the intermediate target, and only 19 stable cases when M2 is used. The results are considerably better in the Keynesian model (81 and 98 stable trials, respectively, for nominal GDP and M2 targets). However, the important characteristic of robustness across alternative models is lacking when the full range of combinations of proportional and derivative control is considered.

It is not entirely surprising that there is a tendency for the models to produce more cases of dynamic instability when an interest rate instrument is used than when the base is used. As noted above, economic theory predicts that the price level would be determinate in the long run and the economy dynamically stable if the monetary authority were to peg the base, but that the price level would be indeterminate and the economy dynamically unstable if the authority were to peg a nominal interest rate at a constant level. Although the feedback rules attempt to avoid this problem by tying interest rate changes to intermediate targets for nominal variables, the underlying tendency toward instability shows through in our results.

However, in the case of an interest rate rule that exerts derivative control only—so that policy responds only to the growth rates, and not the levels, of nominal GDP and M2—there does not appear to be a problem with instability. As Table 1 shows, the model is dynamically stable in all 8 trials when the intermediate target is M2, and in almost all trials (7 out of 8) when nominal GDP is the target.

Counterfactual Simulations

In this section we present the results of simulations that attempt to assess how the macroeconomy might have evolved over the past three decades if the various feedback rules had been in use. In these "counterfactual experiments," the targeted values of the intermediate target variables were set under the assumption that the Fed's goal was to hold the price level constant over 1960–1989. We chose values for α and β that produced stable simulations across the two models. For each combination of rule and model, we calculated 500 stochastic simulations.[8] The random shocks in each equation were drawn from probability distributions that had the same mean and variance as the estimation error terms. Each set of 500 simulations is called an experiment.

In presenting the results of these experiments, we focus on two measures of economic performance that should reflect the concerns of policymakers—the price level and the short-run growth rate of real GDP. Ideally, a policy rule should deliver price stability without causing unacceptable fluctuations in real GDP growth. To address possible concerns about the short-run variability of the interest rate under the rules, we also examine quarter to quarter changes in the interest rate instrument.

We measure the price level performance of each rule in terms of the average inflation rate that it produced over the 30-year simulation period. The volatility of real GDP is measured in terms of the four-quarter growth rate of real GDP. For each experiment, we calculated 95 percent confidence intervals for both of these variables. In the case of the simulations using the interest rate instrument, we also calculated 95 percent confidence intervals for the quarterly changes in the interest rate.

Table 2 shows the performance of the various rules in stabilizing the price level.[9] Using the monetary base as the instrument, adoption of the nominal-GDP feedback rule could have stabilized prices in the long run within narrow limits. For example, under the base rule with both proportional and derivative control ($\alpha = 0.25$ and $\beta = 0.50$), average inflation (with 95 percent probability) would have been between -0.4 and $+0.3$ percent in the Keynesian model and between -0.8 and $+0.7$ percent in the VAR. Under the policies actually followed during this period, average inflation was 5.4 percent.

The rules in which the interest rate is used as the instrument also are able to produce confidence bands that generally are centered near an average inflation rate of zero. However, these bands are wider than when the monetary base is used as the instrument. For example, under the interest rate instrument (with either proportional control alone or both derivative and proportional control), the width of the confidence bands ranges from 1.1 to 4.2 percentage points compared with band widths of 0.7 to 1.5 percentage points when the base is the instrument. Thus although both instruments produce confidence bands for average inflation that are centered on zero, use of the base as the policy instrument reduces price level uncertainty more than use of the interest rate.

[8]There are nine alternative rules (i.e., three combinations of intermediate targets and instruments, and three combinations of α and β) and two models. Thus eighteen sets of 500 stochastic simulations were computed.

[9]The average inflation results in Table 2 are not qualitatively changed if alternative horizons, such as five, ten or twenty years, are used for the stochastic simulations.

Table 2

Simulated Average Annual Inflation Rate 1960–1989

Rule	95% Confidence Limit		
Intermediate Target/Instrument	Proportional Only	Proportional and Derivative	Derivative Only
Nominal GDP/Interest Rate	($\alpha = 0.75, \beta = 0.00$)	($\alpha = 0.25, \beta = 0.50$)	($\alpha = 0.00, \beta = 0.50$)
Keynesian Model	−0.6% to 0.5%	−1.3% to 0.9%	−2.3% to 4.9%
VECM	Explosive	−1.0% to 2.5%	−0.3% to 3.1%
M2/Interest Rate	($\alpha = 0.75, \beta = 0.00$)	($\alpha = 0.60, \beta = 0.25$)	($\alpha = 0.00, \beta = 0.50$)
Keynesian Model	−0.8% to 1.0%	−0.9% to 1.0%	−1.5% to 3.2%
VECM	Explosive	−1.2% to 3.0%	−0.2% to 3.5%
Nominal GDP/Monetary Base	($\alpha = 0.50, \beta = 0.00$)	($\alpha = 0.25, \beta = 0.50$)	($\alpha = 0.00, \beta = 0.50$)
Keynesian Model	−0.4% to 0.3%	−0.4% to 0.3%	−0.2% to 0.7%
VAR	−0.8% to 0.7%	−0.8% to 0.7%	−0.5% to 1.0%
Actual Data:		5.4%	

The confidence bands on average inflation are considerably wider under the interest rate rules if policy exerts only derivative control (see the right-hand column of Table 2). When policy attempts to control only the *growth rate* of the intermediate target, misses in the level in effect are "forgiven" each quarter. Not surprisingly, the widths of the resulting confidence bands on long-run inflation increase to between 3.4 and 7.2 percentage points. However, it is important to note that even at the top ends of these confidence bands, average inflation is below the actual inflation rate over 1960–1989.

Finally, the results suggest that there is little to distinguish the nominal GDP target from the M2 target under an interest rate instrument. However, our use of a sample period that ends in 1989 abstracts from the widely discussed problems with instability in the demand for M2 that have occurred in 1990–1992 (Furlong and Judd 1991, Judd and Trehan 1992). Since 1989, the velocity of M2 has been roughly constant, whereas historical relationships suggest that it should have declined rather sharply in response to declining nominal interest rates. This apparent shift in M2 demand raises concerns that the future performance of M2 as an intermediate target may be worse than it was in the past.

Table 3 shows the effects of the rules on the volatility of real GDP. For each model, it reports 95 percent confidence intervals for four-quarter growth rates of real GDP under the alternative rules.[10] The table compares the simulation results with the distribution of the actual historical data, which is a measure of the volatility of real GDP during the sample period under the discretionary policies actually followed by the Federal Reserve.

In nearly every case, the confidence bands are wider under the rules that use some proportional control (either alone or in combination with derivative control) than they were in the actual sample period, though in some cases the differences are small. For example, in the Keynesian model, use of the nominal GDP/base rule with both proportional and derivative control is estimated (with 95 percent confidence) to yield four-quarter real GDP growth rates of between −4.0 and +10.3 percent, which is wider than the −1.9 to +7.9 percent band in the historical data. In the VAR, the corresponding confidence interval is +0.4 to +9.3 percent, which has about the same width as the historical measure.

Table 3 suggests that use of an interest rate instrument, with at least some proportional control, would lead to larger fluctuations in real GDP growth than a base instrument. The confidence bands are substantially wider under rules that use an interest rate instrument than with a base

[10]We also looked at the volatility of the two-quarter and eight-quarter growth rates of real GDP. The conclusions were qualitatively the same as for the four-quarter growth measures.

Table 3

Simulated Four-Quarter Real GDP Growth Rates

Rule	95% Confidence Limit		
Intermediate Target/Instrument	Proportional Only	Proportional and Derivative	Derivative Only
Nominal GDP/Interest Rate	(α = 0.75, β = 0.00)	(α = 0.25, β = 0.50)	(α = 0.00, β = 0.50)
Keynesian Model	−16.7% to 20.6%	−6.3% to 19.7%	−1.3% to 8.2%
VECM	Explosive	−11.7% to 19.8%	−0.6% to 10.2%
M2/Interest Rate	(α = 0.75, β = 0.00)	(α = 0.60, β = 0.25)	(α = 0.00, β = 0.50)
Keynesian Model	−7.2% to 13.6%	−4.7% to 10.6%	−1.6% to 8.3%
VECM	Explosive	−16.4% to 15.3%	0.8% to 10.0%
Nominal GDP/Monetary Base	(α = 0.50, β =0.00)	(α = 0.25, β =0.50)	(α = 0.00, β = 0.50)
Keynesian Model	−3.4% to 10.0%	−4.0% to 10.3%	−3.5% to 10.2%
VAR	−0.4% to 9.9%	0.4% to 9.3%	0.6% to 9.0%
Actual Data:		−1.9% to 7.9%	

instrument, especially in the VAR and VECM models. There appears to be a slight tendency for the confidence bands to be narrower under an M2 rule than a nominal GDP rule, but the difference is small.

However, *if only derivative control is exerted*, the width of the confidence bands on real GDP growth is noticeably narrower than when there also is a significant element of proportional control (see the right hand column of Table 3). In most cases, derivative control leaves the volatility of GDP at about the same level as it was historically. This is true whether an interest rate or a monetary base instrument is used.

In Table 4, we present evidence on the quarter-to-quarter volatility of the short-term interest rate that might result from following the two rules that use the interest rate as the instrument. When at least some proportional control is used, the rules result in an increase in short-run interest rate volatility compared with that experienced under the discretionary policy pursued in our sample period. Thus the width of the 95 percent confidence intervals varies from 5.2 to 16.9 percentage points under the rules, compared with a width of 4.0 percentage points in the actual data. However, use of derivative control only is estimated to reduce interest rate volatility compared with history. As shown in the right-hand column, the confidence bands range in width from 1.3 to 2.4 percentage points compared with the 4 point width in the actual data.

In summarizing the results in Tables 2, 3, and 4, it is useful to compare the simulations under an interest rate instrument both with those under a base instrument and with the historical record. Compared to the base-instrument results, we conclude:

1. Use of the interest rate permits much more long-run drift in the price level than use of the base.
2. An interest rate instrument also results in more volatility of real GDP, except in the case of derivative control only, when the interest rate instrument leads to less volatility.

Comparing the results under an interest rate instrument with historical experience, we can make the following generalizations:

1. If at least some proportional control is used, the interest rate rule would hold inflation well below its historical average, but would result in greater volatility in real GDP and interest rates than experienced in the past.
2. If derivative control only is used, then the interest rate rules would hold inflation somewhat below historical experience, maintain real GDP volatility at about its historical level, and result in less interest rate volatility than actually occurred in the past.

Table 4

Simulated Quarter-to-Quarter Changes in the Short-Term Interest Rate

(percentage points)

Rule	95% Confidence Limit		
Intermediate Target/Instrument	**Proportional Only**	**Proportional and Derivative**	**Derivative Only**
Nominal GDP/Interest Rate	($\alpha = 0.75, \beta = 0.00$)	($\alpha = 0.25, \beta = 0.50$)	($\alpha = 0.00, \beta = 0.50$)
Keynesian Model	−8.3% to 8.6%	−3.7% to 3.8%	−1.1% to 1.3%
VECM	Explosive	−2.5% to 2.7%	−0.9% to 1.1%
M2/Interest Rate	($\alpha = 0.75, \beta = 0.00$)	($\alpha = 0.60, \beta = 0.25$)	($\alpha = 0.00, \beta = 0.50$)
Keynesian Model	−5.7% to 6.0%	−3.0% to 3.0%	−0.8% to 0.9%
VECM	Explosive	−3.5% to 3.7%	−0.6% to 0.7%
Actual Data:		−2.0% to 2.0%	

Robustness

One problem with attempting to evaluate empirically the likely effects of monetary policy rules that were not actually followed during the period for which data are available is that the estimated behavioral parameters of models might have been different if the rule had actually been used (Lucas 1973). In a crude attempt to deal with this issue, we have recalculated many of the simulations discussed above under alternative assumptions about key coefficients in our estimated models. We ran these simulations under the assumption that selected coefficients varied (one at a time) from their estimated levels by plus and minus two standard deviations. The results of these alternative simulations are shown in Appendix B.

The coefficients that were varied in these tests included the following:

1. In the Keynesian model, we altered the slope of the Phillips curve, the elasticities of real GDP with respect to both real M2 and the real base in the aggregate demand equations, and the interest elasticities of the demand for both M2 and the base. In addition, we varied the length of the lags on past inflation in the Phillips curve, restricted the sum of these coefficients on past inflation to unity, and introduced a unit root in potential GDP.

2. In the VECM, we varied the interest rate, GDP and price elasticities of M2 in the cointegrating vector that appears in the M2 and price equations.

There are too many results in Appendix B to review in detail. However, several general points stand out. First, the results for average inflation are quite robust for all of the rules within all of the models. When the monetary base is the instrument, the results for real GDP growth also are robust, although somewhat less so than for inflation.

As shown in Tables B.2 and B.4, the width of the confidence bands for four-quarter real GDP growth is relatively sensitive to coefficient variations when the interest rate is used as the instrument and the rule involves some proportional control. In a few cases the bands become somewhat narrower, but in many more they become considerably wider. On the other hand, interest rate volatility is relatively less sensitive to the changes in the models' coefficients. However, as shown in Tables B.3 and B.5, when the interest rate rule involves derivative control only, the simulation results are highly robust.

One issue of special concern is the restriction in the Phillips curve that the coefficients on lagged inflation sum to unity (point 2 in Tables B.1, B.2, and B.3). This restriction ensures that monetary policy is neutral with respect to real GDP in the long run (i.e., it makes the Phillips curve "vertical" in the long run), and is a central feature of the theory underlying the Phillips curve. Although the restriction is rejected by the data in our sample (see the F test under equation A.2′ in the Appendix), we imposed it in our sensitivity analysis because of its theoretical importance. In most cases, the imposition of this restriction leads to dynamic instability.

IV. Conclusions

In this paper, we have examined the effectiveness of nominal feedback rules that link short-run monetary policy actions to an intermediate target with the ultimate goal of controlling inflation in the long-run. Two subsidiary goals are that the rules not induce unacceptably large variations in real GDP or in interest rates. Given uncertainties about the structure of the economy, these rules are designed to be model-free in the sense that the monetary authority does not need to rely on a specific model of the economy in order to implement them. In addition, the rules are operational in that they define specific movements in an instrument that can be controlled precisely by the central bank.

We have focused mainly on rules that use a short-term interest rate as the policy instrument, and either nominal GDP or M2 as the intermediate target. As a standard of comparison, we also have looked at a rule in which the monetary base is the instrument and nominal GDP is the intermediate target. This rule has been shown to have desirable properties in earlier research. In addition, we compare the results from the rules with actual experience over the past three decades.

Our empirical results suggest that all of the feedback rules examined, so long as they do not produce explosive paths, would be highly likely to hold inflation below the average rate experienced in the U.S. over 1960–1989. When comparing rules with alternative instruments, the interest rate rule does not measure up to rules with the monetary base as the instrument and nominal GDP as the intermediate target. The latter rule provides much tighter control of the price level and induces somewhat less volatility in real GDP than rules using an interest rate as the instrument. Moreover, rules using the base as the instrument are consistent with dynamic stability in the economy under a wide range of assumptions, whereas the same cannot be said for rules with interest rate instruments. In a number of cases, the latter rules induced explosive paths in the economies simulated.

Despite the strong results obtained for rules with a base instrument, there are reasons to be concerned that their performance in the future would not measure up to the results obtained in our counterfactual simulations covering the past three decades. One important consideration is that the increase in foreign demand for U.S. currency in recent years may have made the overall demand function less stable than in the past.

So, what conclusions can be reached about the effectiveness of rules defined in terms of an interest rate instrument? First, within such rules, nominal GDP and M2 were found over our 1960–1989 sample period to function about equally well as intermediate targets. Given this result, and the evidence that the relationship between M2 and spending may have broken down during 1990–1992, rules defined in terms of nominal GDP would appear to be less risky.

Second, based upon our simulations, interest rate rules that involve some proportional control of nominal GDP (or M2) do not appear to be viable alternatives for monetary policy. We found a large number of cases in which these rules produced explosive paths for the simulated economy. Thus use of such a rule in the real world, where we do not know with any precision the structure and size of parameters of the pertinent behavioral relationships, would run a significant risk of inducing dynamic instability.

However, feedback rules with an interest rate instrument that focus on the growth rate, rather than the level, of nominal GDP (or M2) lead to dynamic stability in the various models. Naturally, such rules automatically accommodate past misses of the level of the intermediate target, and thus allow the possibility that the price level may drift over time. Such drift would occur only when there were a prolonged series of positive or negative shocks. However, it should be noted that even after allowing for such drift, the worst case simulation that we obtained still held the simulated average inflation rate over 1960–1989 below the historical average. Moreover, such an approach is estimated with a very high probability to involve about the same level of volatility in real GDP and a reduction in interest rate volatility compared with historical experience.

This conclusion suggests that, although a rule that aimed at controlling the growth rate of nominal GDP with an interest rate instrument is far from ideal, it might be an improvement over a purely discretionary interest rate policy. It would seem to offer the likelihood of lower long-run inflation without increasing the volatility of real GDP or interest rates. A simple version of such a rule can be written[11]

$$\Delta R_t = -0.50[\Delta x^*_{t-1} - \Delta x_{t-1}].$$

Such a rule could make a contribution to policy, even if it were used only to modify the Fed's traditional discretionary approach. When using an interest rate instrument within the context of a purely discretionary policy, it is natural for the policymaker to evaluate alternative policy actions relative to a status quo policy of leaving the interest rate (currently the federal funds rate) unchanged. As a

[11]As noted above, Δx refers to a change in the log of nominal GDP, while ΔR refers to a change in the interest rate expressed as a percent. Thus when nominal GDP growth deviates from its target by 1 percent (4 percent annual rate), the rule calls for a change in the interest rate of .005, or 50 basis points.

result, the debate tends to focus on a decision about whether the funds rate should be raised or lowered from its recent level. This approach may be misleading, since a policy of leaving the funds rate unchanged does not necessarily imply that the future thrust of policy relative to key macroeconomic variables will remain unchanged.

However, the instrument setting given by the feedback rule at any point in time *does* provide a sensible way to define no change in monetary policy, since it represents a consistent policy regime, incorporating the long-run goal, the intermediate-run target and the short-run instrument. A debate that focused upon whether policy should ease, tighten, or remain the same *relative to what the feedback rule calls for*, would seem to be more informed than one that focused upon whether the short-term interest rate should be changed from recent levels. Occasional adjustments to the nominal GDP target could be used to offset drift in the price level that may arise from exercising derivative control (only) of nominal GDP.[12]

The approach outlined above could be considered as one possible step to improve a purely discretionary interest rate policy. In effect, the rule would be used to provide policymakers with information that could help them make short-run discretionary decisions without losing sight of the long-run goal of controlling inflation.

[12]If, for example, the level of prices were to drift significantly upward or downward despite following the rule, an offsetting adjustment could be made to the path of the nominal GDP target. Of course, the central bank would have to guard against the temptation to make frequent adjustments to the target path, since this could undermine the value of the feedback rule. One way to do this would be to define in advance the amount of drift in the price level that would be tolerated before a level adjustment would be made to the nominal GDP target.

Appendix A
Macroeconomic Models

We employed two alternative sets of assumptions about the structure of the economy: a Keynesian model and a vector autoregression (VAR) or vector error correction model (VECM). As will become apparent, the models are not attempts to describe the structure of the economy as precisely as possible. Rather, the Keynesian model incorporates the fundamental features of this macroeconomic paradigm. The VAR/VECM system is an atheoretic model that captures the statistical relations among various macroeconomic time series. These models are meant to illustrate the basic nature of the responses of the economy to the implementation of the monetary policy rules tested.

All of the equations below are estimated over 1960.Q1 to 1989.Q4. The variables in the regressions below are defined as follows:

b = log of monetary base (adjusted for reserve requirement changes)
cc = 1 in 1980.Q2, and 0 elsewhere
g = log of government purchases
$m2$ = log of M2
mm = 1 in 1983.Q1 and 0 elsewhere
p = log of GDP deflator
R = 3-month treasury bill rate
T = time trend
x = log of nominal GDP
y^f = log of real GDP trend (see equation A.3)
y = log of real GDP

Keynesian Model

The Keynesian, or "sticky price" model, consists of four equations. First, the real aggregate demand equation embodies the direct effects of monetary and fiscal policy on macroeconomic activity. In one version, it specifies the growth rate of real GDP as a function of current and lagged growth rates of the real monetary base, real government spending, and its own lagged values:

$$\text{(A.1)}\ \Delta y_t = \underset{(4.45)}{0.0045} + \underset{(2.06)}{0.17\Delta y_{t-1}} + \underset{(4.41)}{0.47(\Delta b_{t-1} - \Delta p_{t-1})} + \underset{(2.52)}{0.016\Delta g_t} - \underset{(-2.52)}{0.016\Delta g_{t-1}}$$

$\bar{R}^2$ = 0.21
SEE = 0.0083
Q = 21.34
$D.F.$ = 116

An alternative version uses M2 as the monetary policy variable:

$$(\text{A.1}') \quad \underset{}{\Delta y_t} = \underset{(3.18)}{0.0033} + \underset{(1.84)}{0.15\Delta y_{t-1}} + \underset{(5.09)}{0.41(\Delta m2_{t-1} - \Delta p_{t-1})} + \underset{(2.36)}{0.014\Delta g_t} - \underset{(-2.36)}{0.014\Delta g_{t-1}}$$

$\bar{R}^2 = 0.25$
$SEE = 0.081$
$Q = 27.26$
$D.F. = 116$

The supply side of the Keynesian model is a simplified Phillips curve, which embodies the essential "sticky price" characteristic of the paradigm. It specifies that the current inflation rate depends on past inflation and the gap between actual and full-employment real GDP ($y - y^f$). Theory suggests that the coefficients on lagged inflation should be constrained to sum to 1, thus ensuring that, in steady state, real GDP will be equal to its full-employment level, and inflation will be constant. However, the data over the sample period used reject this restriction at the 3.3 percent marginal significance level. Our basic model does not incorporate this restriction, but we also show results in which it is imposed (equation A.2′).

$$(\text{A.2}) \quad \Delta p_t = \underset{(1.89)}{0.0014} + \underset{(2.78)}{0.022(y_t - y_t^f)} + \underset{(3.02)}{0.28\Delta p_{t-1}} + \underset{(3.20)}{0.30\Delta p_{t-2}} + \underset{(2.20)}{0.25\Delta p_{t-3}} + \underset{(0.58)}{0.05\Delta p_{t-4}}$$

$\bar{R}^2 = 0.70$
$SEE = 0.0037$
$Q = 22.05$
$D.F. = 113$

$$(\text{A.2}') \quad \Delta p_t = \underset{(2.62)}{0.021(y_t - y_t^f)} + \underset{(3.44)}{0.32\Delta p_{t-1}} + \underset{(3.51)}{0.33\Delta p_{t-2}} + \underset{(2.98)}{0.28\Delta p_{t-3}} + \underset{(0.86)}{0.07\Delta p_{t-4}}$$

$$\text{RESTRICTION : In } \sum_{i=1}^{4} \delta_i \Delta p_{t-i}, \sum_{i=1}^{4} \delta_i \equiv 1.$$

$$F(1,113) = 4.63.$$

$\bar{R}^2 = 0.69$
$SEE = 0.0038$
$Q = 23.20$
$D.F. = 115$

Equation (A.3) defines y^f, the log of full-employment real GDP, as the fitted values of a log linear time trend (T) of real GDP. This equation incorporates the idea, common to Keynesian models, that real GDP is trend stationary.

$$(\text{A.3}) \quad y_t^f = \underset{(846.15)}{7.56} + \underset{(98.9)}{0.007928\, T_t}$$

$\bar{R}^2 = 0.97$
$SEE = 0.0045$
$Q = 1662.32$
$D.F. = 119$

To test for the robustness of the results under a unit root in real GDP, we also estimate the following equation:

$$(\text{A.3}') \quad \Delta y_t = \underset{(4.00)}{0.0051} + \underset{(2.56)}{0.24\Delta y_{t-1}} + \underset{(1.50)}{0.014\Delta y_{t-2}}$$

$\bar{R}^2 = 0.065$
$SEE = 0.0091$
$Q = 27.31$
$D.F. = 116$

Equations (A.4) and (A.5) represent the financial sector of the model, respectively defining the demands for the monetary base and M2 as functions of the aggregate price index, real GDP and a short-term nominal interest rate. As in Miller (1991), we find that M2 is cointegrated with these arguments, whereas the base is not. Thus the base demand equation is specified in first differences, while the M2 demand equation has an error correction form.

$$(\text{A.4}) \quad \Delta b_t - \Delta p_t = \underset{(0.42)}{0.00029} + \underset{(1.15)}{0.064\Delta y_{t-1}} + \underset{(3.40)}{0.17\Delta y_{t-2}} - \underset{(-7.86)}{0.42\Delta R_{t-1}} + \underset{(7.61)}{0.50(\Delta b_{t-1} - \Delta p_{t-1})}$$

$\bar{R}^2 = 0.54$
$SEE = 0.0050$
$Q = 22.83$
$D.F. = 115$

(A.5)
$$\Delta m2_t = \underset{(-2.49)}{-0.079} - \underset{(-3.27)}{0.89 m2_{t-1}} + \underset{(3.27)}{0.89 p_{t-1}}$$
$$+ \underset{(3.27)}{0.95 y_{t-1}} - \underset{(-3.71)}{0.14 R_{t-1}} + \underset{(11.28)}{0.70 \Delta m2_{t-1}}$$
$$+ \underset{(1.93)}{0.17 \Delta p_t} - \underset{(-1.42)}{0.074 \Delta y_t} - \underset{(-4.56)}{0.26 \Delta R_t}$$
$$- \underset{(-2.83)}{0.016 cc_t} + \underset{(5.78)}{0.029 mm_t}$$

$\bar{R}^2 = 0.61$
$SEE = 0.0049$
$Q = 28.16$
$D.F. = 110$

The above equations were combined with the various feedback rules to form three simulation models that were used to generate results discussed in the text:

Nominal GDP/Interest Rate Simulation: Equation 1, with equations A.1, A.2, A.3, and A.4.

M2/Interest Rate Simulation: Equation 2, with equations A.1', A.2, A.3, and A.5.

Nominal GDP/Monetary Base Simulation: Equation 3, with equations A.1, A.2, and A.3.

Vector Autoregression-Error Correction Models

In addition to the model just discussed, we also conducted simulations using an atheoretic framework. For the case in which the monetary base is used as the instrument, we used the following variables: real GDP, the price level, the base and the nominal short-term interest rate. Following Johansen and Juselius (1990) we tested for cointegrating vectors in this system of variables. Finding none, we estimated a VAR with all variables in first differences. We selected lag lengths using the Final Prediction Error procedure (Judge, et al., 1985). The estimation results are summarized in Table A.1.

The VAR embodies no theoretical restrictions and therefore is agnostic about the structure of the economy. In simulating this model with the nominal GDP/Base rule, the estimated equation for the base was replaced by equation (3) defining the policy rule. This produced:

Nominal GDP/Monetary Base Simulation: Equation 1, together with the VAR equations for y, p, and R.

To evaluate the rules in equations 1 and 2, which use the interest rate as the instrument, we incorporated the following variables: real GDP, the price level, M2, and the

Table A.1

Marginal Significance Levels of Dependent Variables

	Δy	Δp	ΔR	Δb
Δy	.509	—	.000332	—
Δp	.018	.000	.168	—
ΔR	.00192	.0152	.898	.000
Δb	.666	.0366	—	.000
$\bar{R}^2$	0.36	0.71	.039	.063
SEE	0.0080	0.0036	.0077	0.0035
Q	26.55	26.60	43.18	27.85
$D.F.$	101	109	102	110

Table A.2

Vector Error Correction Model

	Dependent Variables			
	Δy	Δp	$\Delta m2$	ΔR
y_{t-1}	—	-0.033^a (−1.66)	0.13^a (3.80)	—
p_{t-1}	—	-0.033^a (−1.66)	0.13^a (3.80)	—
$m2_{t-1}$	—	0.033^a (1.66)	-0.13^a (−3.80)	—
R_{t-1}	—	0.028 (0.26)	−0.11 (−3.55)	—
	(Marginal Significance Levels)[b]			
Δy	.585851	.332590	.237394	.003320
Δp	.004468	.000000	.225075	.168222
$\Delta m2$	.037828	.585279	.000000	—
ΔR	.063848	.004459	.000037	.898220
$\bar{R}^2$	0.31	0.69	0.66	0.32
SEE	0.0078	0.0036	0.0046	0.0077
Q	34.13	17.44	28.60	43.18
$D.F.$	95	103	97	102

[a]Restriction of coefficient equality imposed.
[b]Lags chosen by Final Prediction Error procedure (Judge, et al., 1985).

treasury bill rate. In this case, the Johansen-Juselius tests detected one cointegrating vector, which was statistically significant in the M2 and price equations. Given the signs and magnitudes of the coefficients in this vector, it appears to be a money demand equation. Moreover, the Johansen-Juselius test failed to reject the hypothesis that the coefficients on *y*, *p* and *m2* were equal. The estimation results are summarized in Table A.2.

In simulations to evaluate equations 1 and 2, the interest rate equation above was replaced by the rule. This yielded:

Nominal GDP/Interest-Rate Simulation: Equation 1, together with VECM equations for y, p, and M2.

M2/Interest-Rate Simulation: Equation 2, together with VECM equations for y, p, and M2.

APPENDIX B
SENSITIVITY ANALYSIS: 1960–1989

Table B.1

Rule: Nominal GDP/Monetary Base
Model: Keynesian

		95% Confidence Limits[b]	
	Dynamic Stability[a]	Average Inflation	Four-Quarter Real GDP Growth
1. **Basic Model**	107	−0.4% to 0.3%	−3.4% to 10.0%
Modifications			
2. (A.2′):			
In $\sum_{i=1}^{n} \delta_i \Delta p_{t-i}$, $\sum_{i=1}^{n} \delta_i \equiv 1$	80	−1.1% to 0.4%	−8.9% to 12.6%
3. (A.2):			
One lag of Δp_{t-i}	107	−0.4% to 0.3%	−6.0% to 12.7%
Eight lags of Δp_{t-i}	107	−0.3 to 0.3	−2.8 to 9.6
4. (A.2):			
$\partial \Delta p / \partial (y - y^f)$			
$+2\sigma$	106	−0.4% to 0.1%	−4.3% to 11.0%
-2σ	107	−0.1 to 1.3	−3.1 to 9.8
5. (A.1):			
$\partial \Delta y / \partial (\Delta b - \Delta p)$			
$+2\sigma$	94	−0.4% to 0.6%	−3.7% to 10.3%
-2σ	81	−0.5 to 0.6	−9.9 to 11.0
6. (A.3):			
Use (A.3′)	107	−0.4% to 0.2%	−3.6% to 10.0%

[a]This column reports the number of combinations of α and β that produced dynamically stable simulations out of a total of 107 combinations tried.
[b]Simulations use $\alpha = 0.50$ and $\beta = 0.00$.

Table B.2

Rule: Nominal GDP/Interest Rate
Model: Keynesian

		95% Confidence Limits[b]		
	Dynamic Stability[a]	Average Inflation	Four-Quarter Real GDP Growth	One-Quarter Interest Rate Change
1. **Basic Model**	82	−1.3% to 0.9%	−6.3% to 19.7%	−3.7% to 3.8%
Modifications				
2. (A.2′):				
In $\sum_{i=1}^{n} \delta_i \Delta p_{t-i}$, $\sum_{i=1}^{n} \delta_i \equiv 1$	14	Explosive	Explosive	Explosive
3. (A.2):				
One lag of Δp_{t-i}	77	−1.4% to 2.0%	−26.5% to 23.8%	−6.5% to 7.1%
Eight lags of Δp_{t-i}	77	−0.6 to 1.0	−5.7 to 10.3	−2.5 to 3.0
4. (A.2):				
$\partial \Delta p / \partial (y - y^f)$				
$+2\sigma$	70	−1.4% to 3.0%	−38.3% to 17.5%	−6.0% to 6.8%
-2σ	81	−0.5 to 1.6	−3.9 to 11.5	−2.4 to 3.1
5. (A.1):				
$\partial \Delta y / \partial (\Delta b - \Delta p)$				
$+2\sigma$	38	−0.7% to 0.6%	−7.5% to 15.4%	−2.7% to 3.2%
-2σ	95	−1.2 to 2.7	−13.4 to 12.4	−5.6 to 6.3
6. (A.4):				
$\partial (\Delta b - \Delta p) / \partial \Delta R$				
$+2\sigma$	49	−1.5% to 1.4%	−8.4% to 19.7%	−4.7% to 5.2%
-2σ	101	−1.0 to 0.7	−5.7 to 15.8	−3.1 to 3.2
7 (A.3):				
Use (A.3′)	72	−1.1% to 0.8%	−9.1% to 16.1%	−3.8% to 4.0%

[a]This column reports the number of combinations of α and β that produced dynamically stable simulations out of a total of 107 combinations tried.
[b]Simulations use $\alpha = 0.25$ and $\beta = 0.50$.

Table B.3

Rule: Nominal GDP/Interest Rate
Model: Keynesian; Derivative Control Only

	Dynamic Stability[a]	95% Confidence Limits[b] Average Inflation	Four-Quarter Real GDP Growth	One-Quarter Interest Rate Change
1. **Basic Model**	7	−2.3% to 4.9%	−1.3% to 8.2%	−1.1% to 1.3%
Modifications				
2. (A.2′):				
In $\sum_{i=1}^{n} \delta_i \Delta p_{t-i}$, $\sum_{i=1}^{n} \delta_i \equiv 1$	1	−6.6% to 6.3%	−2.6% to 11.7%	−1.8% to 1.8%
3. (A.2):				
One lag of Δp_{t-i}	7	−1.9% to 4.9%	−2.2% to 8.9%	−1.4% to 1.7%
Eight lags of Δp_{t-i}	7	−1.9 to 5.2	−2.7 to 9.3	−1.0 to 1.3
4. (A.2):				
$\partial\Delta p/\partial(y-y^f)$				
$+2\sigma$	7	−2.9% to 4.2%	−1.7% to 8.2%	−1.3% to 1.5%
-2σ	7	1.0 to 5.7	−1.5 to 7.2	−0.8 to 1.5
5. (A.1):				
$\partial\Delta y/\partial(\Delta b - \Delta p)$				
$+2\sigma$	5	−0.7% to 4.8%	−2.3% to 9.3%	−1.0% to 1.5%
-2σ	8	−4.3 to 5.3	−0.9 to 7.4	−1.3 to 1.3
6. (A.4):				
$\partial(\Delta b - \Delta p)/\partial\Delta R$				
$+2\sigma$	8	−2.4% to 6.3%	−8.0% to 3.3%	−1.1% to 1.5%
-2σ	6	−1.6 to 4.0	−1.7 to 8.3	−1.1 to 1.3
7 (A.3):				
Use (A.3′)	7	−2.0% to 4.9%	−1.9% to 8.1%	−1.1% to 1.4%

[a]This column reports the number of values of β that produced dynamically stable simulations out of a total of 8 trials.
[b]Simulations use $\alpha = 0.00$ and $\beta = 0.50$.

Table B.4

Rule: Nominal GDP/Interest Rate
Model: Vector Error Correction

	Dynamic Stability[a]	95% Confidence Limits[b]: Average Inflation	95% Confidence Limits[b]: Four-Quarter Real GDP Growth	95% Confidence Limits[b]: One-Quarter Interest Rate Change
1. **Basic Model**	21	−1.0% to 2.5%	−11.7% to 19.8%	−2.5% to 2.7%
Modifications				
2. $\Delta M2$ Equation: Coefficients on $M2$, p, and y				
$+2\sigma$	10	−0.8% to 5.1%	−49.7% to 3.8%	−2.3% to 3.6%
-2σ	13	−6.4 to 1.6	−42.2 to 199.2	−8.5 to 6.3
3. Δp Equation: Coefficients on $M2$, p, and y				
$+2\sigma$	0	Explosive	Explosive	Explosive
-2σ	14	−3.0% to 0.1%	−79.9% to 11.6%	−20.4% to 21.2%
4. $\Delta M2$ Equation: Coefficient on R				
$+2\sigma$	7	−5.0% to 3.3%	−3.4% to 40.8%	−3.0% to 2.5%
-2σ	17	−1.3 to 1.9	−23.9 to 33.0	−4.0 to 4.0

[a]This column reports the number of combinations of α and β that produced dynamically stable simulations out of a total of 107 combinations tried.
[b]Simulations use $\alpha = 0.25$ and $\beta = 0.50$.

Table B.5

Rule: Nominal GDP/Interest Rate
Model: Vector Error Correction; Derivative Control Only

	Dynamic Stability[a]	95% Confidence Limits[b] Average Inflation	Four-Quarter Real GDP Growth	One-Quarter Interest Rate Change
1. **Basic Model**	7	−0.3% to 3.1%	−0.6% to 10.2%	−0.9% to 1.1%
Modifications				
2. $\Delta M2$ Equation: Coefficients on $M2$, p, and y				
$+2\sigma$	8	−8.8% to 12.5%	−2.1% to 11.3%	−0.4% to 1.6%
-2σ	8	−5.1 to −2.2	−2.2 to 7.9	−1.2 to 0.8
3. Δp Equation: Coefficients on $M2$, p, and y				
$+2\sigma$	0	Explosive	Explosive	Explosive
-2σ	8	−6.4% to −3.4%	−0.7% to 8.4%	−1.3% to 0.8%
4. $\Delta M2$ Equation: Coefficient on R				
$+2\sigma$	8	4.4% to 8.9%	−2.0% to 7.0%	−0.6% to 1.4%
-2σ	8	−1.0 to 2.2	−0.6 to 9.4	−1.0 to 1.0

[a]This column reports the values of β that produced dynamically stable simulations out of a total of 8 trials.
[b]Simulations use $\alpha = 0.00$ and $\beta = 0.50$.

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Capital Regulation and Bank Lending

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Bank regulation in general and capital regulation in particular are widely perceived as having become stiffer in the 1990s. The stiffer regulatory environment in turn is argued to have curtailed bank lending. This article determines the extent to which capital standards changed in the 1990s and examines the relationship between capital positions and the bank lending. The empirical results suggest that capital standards did increase in the 1990s. The analysis also shows that bank loan growth rates are positively related to capital-to-assets ratios. Moreover, sensitivity of bank lending to capital positions appears to have increased in the 1990s. Regionally, capital regulation likely had the most pronounced effect on bank lending in New England.

The phasing in of international, risk-based capital standards and the growing concern over the risk-exposure of the deposit insurance system are viewed as precipitating stiffer bank capital regulation in recent years. This stiffening of capital regulation is argued to have restricted bank lending beginning in 1990, and, thereby, contributed to a credit crunch.

Consistent with this view, Federal Reserve surveys on bank lending practices find that many banks tightened credit standards in 1990 and 1991 in part due to the volume of problem loans and capital constraints. In addition, some recent studies find a positive relationship between levels of bank capital and bank loan growth in 1990 (Furlong 1991, Bernanke and Lown 1991, and Peek and Rosegren 1991).[1]

The evidence, however, does not indicate the extent to which the relationship between bank capital and bank lending in recent years marks a change from the past. Capital standards traditionally have been a component of bank regulatory policy, and enforcement of such standards could be expected to have influenced lending by individual banks even prior to 1990. The purpose of this study is to examine the extent to which bank capital regulation has changed in the 1990s and the effect the change has had on the relationship between bank capital and lending. The analysis in this paper differs from past studies by using cross-section time series data for individual banks from across the United States rather than cross-section data for a single time period.

The first section of this study discusses the link between capital regulation and bank lending in terms of the regulatory objective of creating microeconomic incentives for banks that are consistent with limiting the risk exposure of the deposit insurance system. The second section compares effective capital standards among banks by size and chartering authority and examines how bank capital standards have changed. The empirical analysis in the third section looks at how the relationship between the financial conditions of banks and their lending has changed over time and whether the effects on bank lending vary by bank size and by geographic region.

[1]Baer and McElravey (1992) find a positive relationship between banks' capital positions and growth rates in assets.

I. THE LINK

In the U.S. banking system, the roles of the federal deposit insurance system and the bank regulatory agencies parallel those of liability holders in private contracts. The deposit insurance system bears financial liability, and the regulatory agencies have monitoring responsibilities analogous to those of private liability holders.

A major criticism of the current institutional arrangement is that, while the roles may be parallel, the deposit insurance system and the regulatory agencies do not necessarily have the same incentive as private liability holders.[2] Nevertheless, regulatory measures are observed that at least in form resemble those seen in private debt agreements that are intended to control risk-taking.

The most obvious example is capital regulation, which is analogous to private debt covenants constraining leverage. Jensen and Meckling (1976) point out that equity holders in general have an incentive to increase risk once debt has been issued. One method for a firm to increase risk is to increase its leverage. To control that incentive, private debt contracts often include provisions limiting the ability of a firm to dilute its capital position.

The importance of capital regulation in banking *per se* is highlighted by Merton (1977) and the large number of studies spawned by that study, which show that the deposit insurance guarantee is essentially a put option, with the value varying negatively with a bank's capital-to-asset position. The options model of deposit insurance thus implies that, with subsidized deposit insurance, a value-maximizing bank has an incentive to increase leverage indefinitely, thus making it necessary for leverage to be constrained by the enforcement of bank capital requirements.

The enforcement of capital requirements can link a bank's capital position with its lending simply as part of the process of a bank meeting regulatory standards. For example, if bank equity is not perfectly elastic, a bank with too little capital could attempt to improve its capital position by reducing its size, and one way to do that is to decrease loans. Indeed, Keeley (1988) finds that in the 1980s, banks deficient in capital did adjust their capital positions in part by growing more slowly than other banks. More generally, banks with stronger capital positions have more capacity to expand loans and still meet regulatory capital standards.

The recent adoption of risk-based capital standards for banks could reinforce the link between a bank's financial condition and its investment decisions. For example, when determining the level of risk-adjusted assets, a zero weight is given to assets with no default risk, such as Treasury securities, while riskier assets, such as loans, are given higher weights.[3] As a result, for a given level of capital, a bank can increase its risk-based capital-to-asset ratio simply by reducing the volume of loans held in its portfolio and acquiring Treasury securities. Such an adjustment would tend to reduce the growth rate of loans.[4]

The options model of the deposit guarantee also suggests another regulatory rationale for linking leverage and the growth of risky assets such as loans. Merton shows that the value of the deposit insurance guarantee is positively related to the degree of asset or nonleverage risk of a bank. This implies that regulatory policy that takes into account the liability of the insurance system can be expected to extend effort to control nonleverage risk.

Moreover, Furlong and Keeley (1989) show that the positive effect of a rise in nonleverage risk on the value of the insurance guarantee increases with a bank's leverage. That is, with higher leverage and mispriced deposit insurance, a bank would have more incentive to expand nonleverage risk. This suggests that regulatory policy should be most concerned with the expansion of nonleverage risk by institutions with the least amount of capital.

Two ways a bank can increase nonleverage risk are to grow and acquire loans (or other assets) that add to its overall risk or to adjust the composition of its existing portfolio toward riskier assets such as loans. From a regulatory perspective, a link between loan growth and leverage could be rationalized as one way of limiting a bank's ability to exploit the insurance system through either of these two options. Loan growth would be more restricted at banks with less capital since they would have the greatest incentive to increase nonleverage risk.[5]

[2]To the extent that the incentive structure differs, regulatory policy and bank behavior will not necessarily coincide with what would be predicted from models of unregulated, uninsured banks. Indeed, Kane (1989) argues that much of the blame for the thrift crisis in the 1980s and the demise of the Federal Savings and Loan Insurance Corporation falls on the nonmarket incentives structure faced by regulators as well as on the incentives inherent in the deposit insurance system for institutions to take risk.

[3]Risk-based capital standards assign risk weights to all bank assets. The weights are determined by considering the credit (default) risk of assets. For example, the lowest risk category includes cash and U.S. Treasury securities, and has a zero weight, which means holdings of these securities do not add to a bank's risk-adjusted assets. The highest risk category includes most loans to private entities (but not home mortgage loans) and has a weight of 100 percent. The standards also account for credit risk of *off-balance* sheet activities such as interest rate swaps and stand-by letters of credit.

[4]Under the risk-based standards, banks also are subject to a leverage ratio requirement, which is a ratio of capital to balance sheet assets including Treasury Securities. Thus, a bank would not be able to increase leverage indefinitely by shifting to assets with a zero weight.

[5]Bernanke and Gertler (1987) show that the financial condition of uninsured, unregulated banks also could be expected to affect their lending. In their model, banks invest in loans (risky assets) because they

II. CHANGING CAPITAL STANDARDS IN THE 1990S

Capital regulation has always played some role in bank regulatory policy. Over the past several years, however, the theoretical arguments connecting capital and bank risk and the more concrete evidence of the problems in the thrift and banking industries, which ultimately led to the demise of the FSLIC and the "recapitalization" of the bank insurance fund, heightened the awareness of the importance of equity in banking.

This awareness was reflected in the adoption of explicit minimum regulatory capital ratios for all but the largest banks in 1981 and the subsequent raising and extending of the minimum ratio to all banks in 1985. In an evaluation of the effects of the changes in capital standards during the first half of the 1980s, Keeley (1988) finds that they were effective in raising capital-to-asset ratios for publicly traded banks with low capital ratios.

Since 1985, additional important steps have been taken to place capital regulation at the center of regulatory policy. One in particular was the adoption of risk-based capital standards by the bank regulatory agencies.[6] The phase-in of these standards started in 1990 and it will be completed at the end of 1992. When fully phased in, the risk-based standards will require banks to maintain a minimum 4 percent ratio of Tier 1 capital to risk-adjusted assets, and an 8 percent ratio for Tier 1 plus Tier 2 capital. To be considered well capitalized, however, a bank would have to exceed the minimum ratios.[7] Tier 1 capital consists primarily of common equity, while Tier 2 capital can include subordinated debt and such instruments as cumulative perpetual preferred stock.

Since the current capital standards use a risk-adjusted measure of assets, the capital requirements under the current standards are not directly comparable to ratios associated with the standards applied in the 1980s. However, it is still possible to evaluate whether the new standards have led to more stringent regulatory regimes in terms of leading banks to hold more capital relative to what they held in the past.[8] To do so, this study examines the impact of regulatory policy on banks' ratios of equity-capital to total assets. This study assumes that banks have target equity-capital-to-asset ratios and that they adjust to those targets gradually over time. The adjustment process for bank i can be written as:

$$k_{i,\,t} - k_{i,\,t-1} = a(k^{*}_{i,\,t} - k_{i,\,t-1}),$$

where, k is the actual capital-to-asset ratio, k^* is the target ratio, and a is the rate of adjustment.

In the model, it is assumed that capital regulation is binding and that k^* reflects the level of capital the regulator views as appropriate given the nonleverage risk of the bank.[9] The target ratio, however, is not necessarily a minimum ratio or a required regulatory ratio. For example, if there are regulatory costs imposed on a bank that has a ratio below the level deemed appropriate by the regulator, the bank may choose to hold additional capital as a buffer against shocks to equity. The target ratio for the bank also would reflect such a buffer. Finally, the partial adjustment process implies that adjusting capital is costly.

With data on the actual capital ratios, the expression above was used to estimate average target ratios and rates of adjustment for various groupings of banks. Average target ratios and adjustment parameters were estimated for all banks, for large and small banks separately, and for national and state chartered banks. If capital regulation became stiffer in 1990, the average target ratios or rates of adjustment would be expected to have increased.

The data used for estimation are from year-end Call Reports for commercial banks over the period 1985 through

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have more information on loans than do liability holders and the information cannot be transferred. Given the information asymmetry on risky investments, the capital of a bank is necessary to assure liability holders that the bank would be able to make good on the promised return to depositors. Assuming a bank's capital equity is not perfectly elastic, a negative shock to a bank's capital could impair its ability to meet its obligation to liability holders unless the bank also shifts its investment portfolio toward riskless assets and away from risky assets. This says that the adequacy of a bank's capital would affect the makeup of its portfolio.

[6] The prominence of capital regulations was heightened further by the Federal Deposit Insurance Corporation Improvement Act (FDICIA) of 1991, which directs the regulatory agencies to use the risk-based capital standards to trigger specific regulatory responses in a protocol called "prompt corrective action." Under the protocol, as a bank's capital falls, the bank faces more restrictions and the regulatory agencies have less flexibility in dealing with the bank.

[7] Using the current risk-based capital standards, the FDICIA established five categories that are intended to reflect banks' capital adequacy. The five categories are: (1) *well-capitalized,* which includes institutions that significantly exceed the capital requirements; (2) *adequately capitalized,* which includes banks meeting all requirements; (3) *undercapitalized,* which includes banks not meeting at least one capital requirement; (4) *significantly undercapitalized,* which includes banks well below at least one capital requirement; and (5) *critically undercapitalized,* which includes banks falling below a predetermined critical capital level.

[8] A general shift in bank portfolios could complicate comparisons over time. In recent years, the most obvious shifts in banking have been to Treasury securities and home mortgages. Under the risk-based standards, these assets have weights of less than 100 percent and an increase in their relative importance in bank portfolios could mask a shift to move stringent capital regulation.

[9] In recent years, it is possible that some banks have been impelled to improve capital positions by market pressures rather than by regulatory requirements.

1991. The data are for banks with assets of $100 million or more. Banks that acquired other banks in particular years are excluded from the sample for those years.[10]

The results from estimating the capital ratio adjustment equation for the various groupings of banks are reported in Table 1. The estimation procedure corrects for heteroskedasticity along the lines of White (1980). The figures in the first column represent estimates of the average target ratios and rates of adjustment for all banks in the sample.[11] The results show that for the period 1985–1989 the target capital-to-asset ratio was about 7.2 percent. For the 1990–1991 period, the ratio increased to about 8.8 percent. The increase in the ratio is statistically significant, and is consistent with a shift to a more stringent regulatory regime after 1989.

The estimate of the average adjustment factor also increases for the 1990–1991 period. However, the decrease is not statistically significant. Thus, while effective capital standards appear to have increased, the rate of adjustment in capital ratios for banks as a group is not indicative of more vigorous enforcement of the new standards.

The table also reports statistics by bank size and charter. Under bank asset size, the target ratios are higher for smaller banks than for larger banks. This is consistent with the view that smaller banks are required to hold more capital to offset their tendency to be less diversified and, thus, have higher nonleverage risk than larger banks.[12] On the other hand, the adjustment parameters are higher for the large banks. This would be the case if regulators enforced capital regulations more stringently for the larger banks. It also could be the case if capital requirements were binding more frequently for large banks than for small banks.

In terms of *changes* in regulatory policy, the target ratios increased for both large and small banks after 1989. The increase is statistically significant for small banks, which is consistent with an escalation in the stringency of capital regulation for those banks. The adjustment parameter for the sample of small banks declined slightly, though the

[10]The sample also excludes banks like credit card banks that do not engage in a broad array of banking activities. The sample also excludes banks with negative capital-to-asset ratios or ratios greater than one half.

[11]Nonlinear adjustment equations also were estimated. The results regarding changes in capital regulation are essentially the same as those shown in table 1. The estimated target ratios, however, are about a percentage point lower across the board.

[12]For example, results in Laderman, Schmidt, and Zimmerman (1991) suggest that small banks tend to lend in local markets and to have less diversified portfolios.

Table 1
Target Capital-to-Asset Ratios and Adjustment Parameters

		By Asset Size			By Charter		
Target Ratio	**All banks**	**$100 million to $1 billion**	**$1 billion or more**	**Difference**	**State**	**National**	**Difference**
1990–1991	0.0880**	0.0923**	0.0740**	0.0183†	0.0961**	.0822**	0.0139
1985–1989	0.0718**	0.0733**	0.0610**	0.0123**	0.0749**	.0664**	0.0085**
Difference	0.0162**	0.0191**	0.0130†		0.0212*	.0158**	
Adjustment Parameter							
1990–1991	0.0738**	0.0561**	0.1474†	−0.0913	0.0445	0.1154**	−0.0709
1985–1989	0.0762**	0.0740**	0.1268*	−0.0529	0.0964**	.0466**	0.0498
Difference	−0.0024	−0.0179	0.0206		−0.0519	.0688‡	

* significant at 5 percent level
** significant at 1 percent level
† significant at 10 percent level
‡ significant at 6 percent level

change is not significant. The target ratio and the adjustment parameter both increased for large banks after 1989, but only the change in the target ratio is statistically significant. The evidence, is then supportive of the hypothesis that capital regulation systematically became more stringent for the large banks.

Looking at banks by type of charter, the increases in the target ratios after 1989 are positive and significant for state-chartered and nationally chartered banks. Based on the changes in the target ratios, the shift in capital regulation was about the same for state-chartered banks as it was for nationally chartered banks, with the difference not statistically significant. The changes in the adjustment parameters, however, are consistent with more of a tightening of regulatory policy for the national banks. The adjustment parameter for the sample of national banks increased, with the change significant at the 6 percent level. For the state-chartered banks, the estimated adjustment parameter declined, but the change was not significant. In evaluating the overall stringency of regulatory policy it can be noted that the level of the target ratio tends to be higher for state-chartered banks.[13]

III. Capital Regulation and Bank Lending

Overall, the results in Table 1 indicate that capital regulation has been more stringent in recent years, which is consistent with regulatory policy that is increasingly concerned with the soundness of the deposit insurance system. The earlier discussion also suggests that such regulatory concerns could be expected to lead to a positive relation between the capital position of a bank and its rate of loan growth. The analysis in this section focuses on this relationship. In particular, it examines whether a bank's capital position affects its lending and whether that relationship has been affected by the shift in regulatory regime suggested by the results in the previous section.

The model used is a reduced form equation for the growth in bank loans:

$$\log\left(L_{i,t}/L_{i,t-1}\right) = f\left[g\left(k_{i,t-1}/k^*_{i,t}\right), X_{i,t}, e_{i,t}\right].$$

This expression says that the growth rate of loans at a given bank depends on the level of the actual capital ratio relative to the target ratio, a set of variables X, which represents other supply and demand factors, and an error term. If capital regulation affects bank lending, loan growth would be expected to be positively related to the spread between the actual and the target capital ratios. If the change in regulatory regime over the past few years has contributed to slower bank loan growth, the positive effect of the spread in the capital ratios on bank loan growth would be expected to have increased.

The other supply and demand variables included in the empirical analysis are the growth rate in personal income for the state in which the bank operates, a bank's ratio of current loans to total loans, and a bank's ratio of total loans to assets. The income variable is intended to control for general economic conditions faced by a bank and is expected to have a positive relation with loan growth. The ratio of current loans also could be an indicator of the economic environment in which a bank operates.[14] A higher ratio could be indicative of a stronger economic environment and could be associated with higher loan growth. This variable also could capture regulatory effects on a bank. Holding capital constant, banks with higher ratios of current loans should be viewed as being stronger financially. If so, the current loan ratio would be expected to have a positive relationship with loan growth. The other variable, the ratio of total loans to assets, is meant to control for the capacity of a bank to boost loan growth by shifting out of other assets in its portfolio. In this regard, the ratio would be expected to have a negative relationship with loan growth. Again, the effect of the loan-to-asset ratio on loan growth may reflect regulatory influences. All else equal, bank regulators could view banks with higher loan-to-asset ratios as being less financially sound and, therefore, may tend to limit the loan growth of such banks.

The basic equation used in estimation is:

$$\begin{aligned}\ln\left(L_{i,t}/L_{i,t-1}\right) = {} & c + B_1\ln\left(INC_{i,t}/INC_{i,t-1}\right)\\ & + B_2\ln\left(P/L\right)_{i,t-1}\\ & + B_3\ln\left(L/A\right)_{i,t-1}\\ & + B_4\ln\left(k_{i,t-1}/k^*_{i,t}\right) + e_{i,t},\end{aligned}$$

where:

L is total loans
INC is the level of the income in the state in which a bank operates
P is current loans
A is total assets
k is the actual equity capital-to-asset ratio, and
k^* is the target equity capital-to-asset ratio.

The target ratios are derived from the capital adjustment equation discussed earlier.[15] The targets differ by size

[13]This result holds up even when controlling for bank size.

[14]These are loans that are less than 30 days past due and accruing interest.

[15]The estimates of k^* from a nonlinear adjustment equation also were used in the loan growth equation. The statistical results are essentially the same as those in Tables 2 through 4.

of bank and by time period. Average targets were estimated separately for small banks ($100 million to $1 billion in assets) and large banks ($1 billion or more in assets) for the 1985–1989 period and the 1990–1991 period. Lagged values were used for P/L and L/A to avoid possible simultaneity problems. Once again, the interval used is one year, and the estimation procedure corrects for heteroskedasticity.

The loan growth equation was estimated over the period 1985 through 1991. The first column of Table 2 shows that the coefficients on state income growth and the quality of a bank's portfolio are positive and highly significant. The loan-to-asset ratio has a negative effect but is not statistically significant.

More central to the focus of this paper, the capital position variable, measured by the ratio of a bank's actual leverage to its target leverage, has a positive and statistically significant effect on bank loan growth. This is consistent with capital regulation having an effect on bank lending. The results for loan quality and the loan-to-asset ratio also may reflect regulatory influences on bank lending. Overall, these results support the view that regulatory policy does limit the loan growth of banks in weaker financial condition.

The last two columns in the table provide evidence on the shift in the behavior of bank lending in recent years and its possible relationship to bank capital regulation. In the second column, the shift in bank loan growth is measured by the coefficient on the bivariate dummy variable $D90\text{-}91$, which takes a value of 1 in 1990 and 1991 and a value of 0 in the earlier years. The coefficient shows a negative and statistically significant shift in the average growth rate of

Table 2

All Banks
Total Loan Growth Regressions

(1985–1991)

Explanatory Variables	(1)	(2)	(3)
c	4.063 (6.05)**	5.778 (8.53)**	5.741 (8.49)**
$\ln\left(\mathrm{INC}_{i,\,t}/\mathrm{INC}_{i,\,t-1}\right)$	1.257 (27.04)**	1.105 (22.74)**	1.104 (22.71)**
$\ln\left(P/L\right)_{i,\,t-1}$	106.948 (19.15)**	109.806 (19.47)**	109.760 (19.47)**
$\ln\left(L/A\right)_{i,\,t-1}$	−1.000 (−1.27)	−1.044 (−1.33)	−1.071 (−1.37)
$\ln\left(k_{i,\,t-1}/k^*_{i,\,t}\right)$	4.952 (7.10)**	3.718 (4.84)**	2.221 (2.53)*
$D90\text{–}91$		−2.535 (−8.52)**	−1.932 (−4.96)*
$\ln\left(k_{i,\,t-1}/k^*_{i,\,t}\right) \bullet D90\text{–}91$			4.373 (2.88)**
$\overline{R^2}$	0.126	0.13	0.131
N	16,261	16,261	16,261

Note: t statistics are in parentheses
* significant at 5 percent level
** significant at 1 percent level

loans in the 1990–1991 period. This result is consistent with the widely held view that bank lending was unusually weak in 1990 and 1991.

To test for a change in the effects of capital regulation, in the third column *D*90-91 is interacted with the log of the ratio of actual leverage to target leverage. The results indicate that the capital position of banks had a positive and statistically significant effect on bank lending even in the second half of the 1980s. This is consistent with other evidence that regulatory policy was emphasizing capital regulation during that period. The connection between capital regulation and bank lending then is not a phenomenon that arose only in the 1990s.

That relationship, however, does appear to have intensified considerably in the past few years. The coefficient for the interacted capital position variable and the dummy variable *D*90-91 is highly significant and points to a relatively large increase in the sensitivity of bank loan growth to capital positions. Overall, the coefficient on the capital position variable is just about three times larger for the period 1990–1991 than for the period 1985–1989. Measured from the average target values, a 0.01 drop in a bank's capital ratio would have lowered its loan growth for a year by an estimated 0.3 of a percentage point during the second half of the 1980s. In the 1990–1991, the same decline in the capital ratio would have led to an estimated 0.8 of a percentage point drop in loan growth.

The finding that bank lending has become more sensitive to capital positions is consistent with a shift to a more stringent regulatory regime in the 1990s.[16] The difference in the coefficient on *D*90-91 between columns (2) and (3) also suggests that the shift in regulatory regime relating to capital regulation may account for part, but not all, of the unusually slow bank loan growth in the 1990 and 1991. The unexplained portion could be due to differences in the behavior of bank lending during recessionary periods, special economic factors such as the condition of the commercial real estate sector, or perhaps more general regulatory influences on bank lending that were not tied directly to capital positions.

Bank Size

To determine how lending may have been affected at different size banks, Table 3 reports pooled cross-section regression results in which separate coefficients are estimated for large and small banks. The coefficients on state income growth indicate that loan growth at small banks is more sensitive to local market conditions. This is not surprising, since bigger banks can be expected to engage in more lending regionally, nationally, and even internationally. Lending by small banks and large banks is about equally sensitive to the quality of loan portfolios.

The effect of the loan-to-asset variable also is different for small and large banks. The effect for small banks is what would be expected for banks with relatively constrained asset/liability management options, such as relying mainly on local, retail deposits. That would make smaller banks with higher loan-to-asset ratios less able to expand lending. The result for smaller banks also is consistent with regulatory policy that tries to constrain nonleverage risk.

For large banks, however, the coefficient for the loan-to-asset ratio is positive, though only marginally significant. One reason for the difference may be that large banks have access to national and even international money and capital markets, so their ability to expand loans is less constrained by the makeup of their existing portfolios. Without this constraint, it may be that the portion of assets invested in loans is an indication of a bank's general investment strategy; banks with high ratios lend more and so tend to have faster loan growth. This is not, however, the relationship that earlier was argued would be expected if this variable were capturing the effects of regulatory policy concerned with controlling nonleverage risk.

The main focus of this analysis is on the effects of capital regulation. The results in Table 3 show that lending by large banks in general is much more sensitive to capital ratios relative to target ratios. This is true even for the 1985–1989 period. In that period, the coefficient for the larger banks is positive and highly significant. In contrast, the coefficient on the capital position variable is positive but not statistically different from 0 for the small bank sample. These results are consistent with the evidence in Table 1 suggesting that capital regulation is more binding for larger banks than it is for smaller banks.

In terms of the shift in regulatory policy, the coefficient on the capital position variable interacted with the shift dummy in the first column of Table 3 suggests that capital regulation has become a factor for small banks in recent years. The point estimate for the increase in sensitivity of lending to capital positions is bigger for the large banks than for the sample of small banks. However, the change for large banks is not statistically significant.

The evidence, then, suggests that the capital regulation has shifted for small banks but perhaps not for larger banks, at least not beyond increases in target capital ratios indicated in Table 1. At the same time, these results suggest that standards under the new capital regulation regime, as

[16]The loan growth equation also was estimated allowing for shifts in the relationship between loan growth and each of the explanatory variables. This had virtually no effect on the change in the coefficient for the capital regulation variable.

under the old, are relatively more binding for the larger banks. Moreover, the larger unexplained decline in loan growth in 1990–1991 for large banks could reflect a shift in regulatory policy toward those banks relative to their smaller counterparts.

Regional Effects

The financial condition of banks varies across geographic regions. The chart, for example, shows that in the early 1990s bank capital positions weakened considerably in New England compared to other regions of the country. The earlier finding of a positive relation between bank capital positions and lending suggests that bank lending should have been more adversely affected in the areas experiencing greater weakness in capital.[17] However, the variation in the financial conditions of banks also raises the possibility that the *shift* in regulatory regime was more pronounced in some geographic regions.

Table 4 presents two sets of statistics relating to the shift in the sensitivity of bank lending to capital positions across regions. The first set consists of estimates from a pooled cross-section time series in which the coefficients in the loan growth equation are constrained to be the same for

[17]In testimony to the U.S. Congress, Richard Syron, President of the Federal Reserve Bank of Boston, argues that the decline in bank capital in the New England area was an important cause of the weakness in lending, and contributed to the so-called credit crunch. See Syron (1991).

Table 3

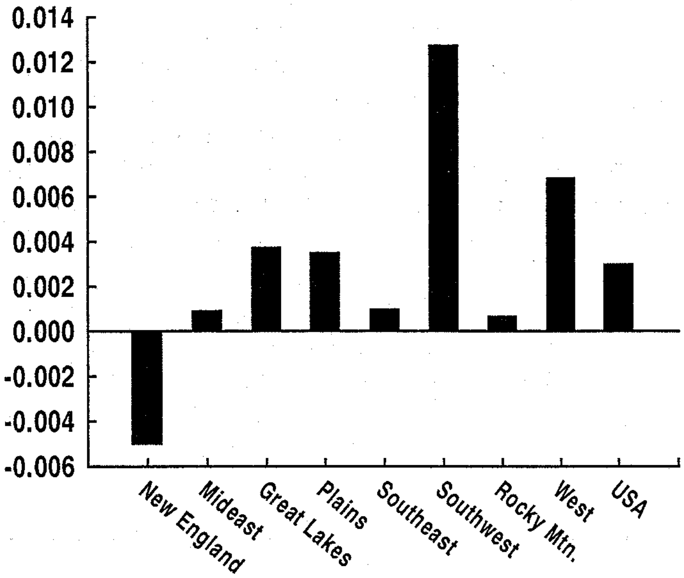
Large and Small Banks Total Loan Growth Regressions

(1985–1991)

Explanatory Variables	By Asset Size: $100 million to $1 billion	$1 billion or more	Difference
c	5.162 (7.20)**	11.238 (6.78)**	−6.076 (−3.36)**
$\ln\left(INC_{i,t}/INC_{i,t-1}\right)$	1.138 (22.29)**	0.740 (4.83)**	0.398 (2.47)*
$\ln\left(P/L\right)_{i,t-1}$	110.570 (18.67)**	92.855 (5.61)**	17.715 (1.01)
$\ln\left(L/A\right)_{i,t-1}$	−1.645 (−2.08)**	4.965 (1.78)	−6.610 (−2.28)*
$\ln\left(k_{i,t-1}/k^*_{i,t}\right)$	1.081 (1.33)	13.100 (2.78)**	−12.019 (−2.53)*
$D90$–91	−1.838 (−5.90)**	−4.929 (−2.72)**	3.091 (1.68)
$\ln\left(k_{i,t-1}/k^*_{i,t}\right) \cdot D90$–$91$	3.680 (3.03)**	5.574 (0.70)	−1.894 (−0.43)
$\overline{R}^2$	0.137		
N	16,261		

Note: See note to Table 2.

The Change in Capital-to-Asset Ratios between 88/89 and 90/91[a]



[a]The differrence between the average of the quarterly data 1988/89 and 1990/91

banks in all regions, with the exceptions of the dummy variable *D*90-91 and the capital position variable interacted with the dummy. To simplify the presentation, only the figures measuring the shifts in the intercept and the coefficient on the capital position variable are reported. The geographic regions correspond to the Bureau of Economic Analysis definitions.[18]

The results suggest that the change in sensitivity of bank lending to capital positions may have been more pronounced in some regions. Only three of the eight regions show statistically significant increases, with the largest change for the New England region. However, some shift also may have occurred in the other regions. For example, when the five regions not showing statistically significant results in the second column of Table 4 are grouped together, we can reject the hypothesis of no change in the loan growth/capital position relationships after 1989.

In the pooled regression for all banks, it is possible that systematic differences among regions prior to 1990 affected the measured shifts in the loan growth equation. Accordingly, the second set of statistics in Table 4 is based on separate cross-section time series regressions for each region. Overall, the results show somewhat more evidence of a shift in the effect of banks' capital positions than do the results for the pooled regression for all banks. The three regions showing significant positive shifts in the coefficient for the capital position variable in the first set of statistics also do so in the second set. One additional region showing a shift in the loan growth/capital position relationship is the Southeast. Another difference is that the Great Lakes region shows a marginally significant increase in the response of bank lending to capital positions in the separate regression for that region.

The separate regressions still suggest regional differences in the shift in regulatory policy, again with the New England region showing the largest increases in the sensitivity of bank lending to capital positions. These results, coupled with the data on the decline in capital positions, highlight why the credit crunch in 1990–1991 is most closely associated with developments in New England. That region shows the largest decline in bank capital ratios and the biggest increase in the sensitivity of lending to capital positions in the 1990–1991 period.

The results for the Southwest region provide an interesting comparison with those for the New England region. The separate regression for the Southwest shows neither a significant shift in the relationship between loan growth and bank capital positions nor a negative intercept shift in the loan growth equation after 1989. This may reflect the improvement in capital positions of banks in the Southwest as illustrated in the chart. More likely, these results reflect the difference in timing of the problems hitting the banks in the Southwest. In that region, the problems in the banking industry hit in the 1980s. As a result, bank loan growth in the Southwest was already weak going into the 1990s. The weakness in banking lending in the Southwest in the 1990–1991 period is reflected in the significant negative shift in intercept in the first column of Table 4.

The evidence for the West also is interesting since it suggests that bank lending became less sensitive to capital positions in the 1990–1991 period. Indeed, with the change in the sensitivity during the 1990–1991 period, the overall effect of bank capital positions on lending was not statistically significant for the West. This does not necessarily mean that the region was unaffected by regulatory policy, however. The regression results for the West do indicate a significant downward shift in loan growth in 1990–1991, which leaves open the possibility that regulatory policy affected lending in the region. It is still possible that regulatory policy had a dampening effect on lending; it is just not evident that such influences were systematically related to the bank capital positions in the area.

IV. CONCLUSION

This paper finds that loan growth for individual banks is positively related to their capital-to-asset ratios. The analysis in this paper goes beyond that of previous studies by

[18]Alaska and Hawaii are included in the West.

using a much broader sample of banks and examining how the relation between capital positions and lending has changed in recent years. The analysis shows increases in both bank capital standards and in the sensitivity of bank lending to capital positions in the early 1990s compared with the second half of the 1980s. The apparent shift in regulatory regime affected small banks as well as large banks. The overall sensitivity of lending to capital positions was more pronounced during both periods for the large banks in the sample. This result is consistent with the view that capital regulation tends to be binding more often for larger banks than for smaller banks. The change in the sensitivity of bank lending to capital positions varies regionally, with the New England region being the most affected.

With regard to the so-called credit crunch in the 1990s, the findings in this paper support the view that the increase in effective capital standards and the actual decline in capital positions of some banks contributed to slow loan growth in the 1990–1991 period. In addition, the increased sensitivity of bank lending to capital positions accounts for a portion of slower than normal bank loan growth in the 1990–1991 period. The impact of capital regulation on lending likely was most pronounced in the New England region, which experienced both the greatest decline in bank capital ratios and the sharpest rise in sensitivity of

Table 4

Regional Effects Total Loan Growth Regression

(1985–1991)

	Pooled Regression For All Banks		Separate Regressions by Region			
	*D*90–91	ln $(k_{i,t-1}/k^*_{i,t})$ • *D*90–91	*D*90–91	ln $(k_{i,t-1}/k^*_{i,t})$ • *D*90–91	$\bar{R}^2$	*N*
New England	1.324 (1.09)	14.966 (4.88)**	−5.300 (−1.44)	20.53 (3.31)**	0.311	790
Mideast	−0.665 (−0.61)	5.143 (1.20)	−6.079 (−4.62)**	4.310 (0.90)	0.118	2504
Great Lakes	−1.205 (−1.73)	3.044 (1.01)	−2.367 (−3.27)	5.328 (1.62)	0.082	4104
Plains	−1.697 (−2.48)*	8.241 (3.22)**	−0.281 (−0.36)	9.783 (3.42)**	0.103	1604
Southeast	−3.586 (−8.46)**	1.724 (1.09)	−4.244 (−8.84)**	6.00 (3.59)**	0.186	3597
Southwest	−4.419 (−2.73)**	3.839 (1.09)	2.116 (1.14)	4.297 (1.12)	0.100	1924
Rocky Mtn.	−4.900 (−2.65)**	12.155 (2.58)**	1.279 (0.63)	13.68 (2.71)**	0.156	529
West	0.521 (0.38)	−4.717 (−0.95)	−4.538 (−2.52)*	−12.742 (−1.82)‡	.063	1209
$\bar{R}^2$		0.135				
N		16,261				

NOTE: See note to Table 2.

lending to bank capital positions. For banks nationally, however, a good portion of the slower loan growth in 1990–1991 is not accounted for directly by movements in capital positions or by changes in capital regulation. The unexplained portion may be due to the difference in the behavior of the supply and the demand of bank loans during recessionary periods, special economic factors such as the condition of the commercial real estate sector, or perhaps more general regulatory influences on bank lending that were not tied systematically to capital positions.

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Macroeconomic Shocks and Business Cycles in Australia

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A small vector autoregression model is estimated to assess how demand and supply shocks influence Australian output and price behavior. The model is identified by assuming that aggregate demand shocks have transitory effects on output, while aggregate supply shocks have permanent effects. The paper describes how Australian macroeconomic variables respond to demand and supply shocks in the short run and in the long run. It also finds that demand shocks are dominant in determining fluctuations in Australian output at a one-quarter horizon, but supply shocks assume the larger role at longer horizons. Supply shocks also account for most of the fluctuations in the Australian price level.

The recession and sluggish growth that have characterized the U.S. economy beginning in the late 1980s have renewed interest in the processes that govern business cycle behavior. Recent studies by Blanchard and Quah (1989), Shapiro and Watson (1988), Judd and Trehan (1989, 1990), and Gali (1992) have used structural vector autoregression models to provide useful insights on U.S. business cycle behavior.[1]

This paper extends their analyses to examine how demand and supply shocks affect business cycle behavior in Australia. The application to Australia is of interest for at least two reasons. First, previous studies give widely differing estimates on the importance of supply and demand shocks in influencing cyclical behavior. A study of Australia may provide further evidence to help clarify this question. Second, a comparison of the evidence from Australia with the results from previous research may highlight similarities or contrasts in business cycle behavior in small open economies and large, relatively closed economies, like the United States.

The paper focuses on three closely related questions: (i) How do macroeconomic variables respond to demand and supply shocks? (ii) How much of the variance in output and inflation is explained by demand and supply shocks? (iii) How do demand and supply shocks influence cyclical behavior, particularly during recessions? These three questions are addressed by estimating a small vector autoregression model of the Australian economy. Unobservable demand and supply shocks are then identified by assuming that aggregate demand shocks have transitory

[1]As discussed below, these studies identify a structural model by using long-run identifying restrictions. Long-run identifying restrictions are also used by Gerlach and Klock (1990) to study Scandinavian business cycles and Moreno (1992a) to study Japanese business cycles. Other studies using such restrictions address somewhat different questions. Hutchison and Walsh (1992) examine the Japanese evidence on the insulation properties of exchange rate regimes, while Hutchison (1992) investigates whether the vulnerability of the Japanese and U.S. economies to oil shocks declined between the 1970s and the 1980s. Another strand of the literature identifies demand and supply shocks by imposing restrictions on the contemporaneous impact of these shocks (Blanchard 1989, Blanchard and Watson 1986, and Walsh 1987).

effects while aggregate supply shocks have permanent effects on output. One advantage of this approach is that it does not assume that short-run fluctuations are entirely due to temporary demand shocks (as in the traditional approach to macroeconomic modeling) or permanent supply shocks (as in early real business cycle models). Instead, the method estimates the relative importance of aggregate demand and supply shocks at various forecast horizons. A second advantage of this approach is that it avoids the imposition of arbitrary identifying restrictions, thus addressing objections raised by Sims (1980). Finally, the paper relies on economic theory to achieve identification, addressing objections to atheoretical VAR methods cited by Cooley and Leroy (1985) or Bernanke (1986).

The description of the dynamic responses of macroeconomic variables to demand and supply shocks obtained by addressing the first question may provide insights that are relevant to policy analysis. At the same time, answers to the second and third questions can shed light on the relative importance of demand and supply shocks in influencing business cycle activity, a question that has acquired prominence in the 1980s with the growing popularity of real business cycle theory. This paper finds that although supply shocks have a strong influence on Australian business cycle behavior, demand shocks still play a significant role.

The paper is organized as follows. Section I provides some background on the Australian economy. Section II describes the model estimated (which closely resembles that used by Shapiro and Watson (1988)) and the identifying restrictions used. Section III discusses the univariate properties of the data, and how these results are used in VAR estimation. Section IV reports the results of VAR estimation and applies them to answer the three questions posed in this introduction. Section V summarizes the findings of this paper and suggests possible extensions.

I. Background

To provide a context for the analysis of Australian business cycles that follows, Table 1 identifies peak-to-trough dates, their duration, average output growth and inflation rates and deviations of these rates from baseline rates during recessionary periods. The baseline rates are based on two subsamples, because statistical tests reported

Table 1
GDP Growth during Recession and Inflation Characteristics of Australia

Peak-Trough Dates	Quarters of Downturn	GDP		Inflation	
		Compound Annual Growth (%)	Deviation from Baseline[a]	Compound Annual Rate (%)	Deviation from Baseline[a]
Full-sample 1960.Q1–1989.Q4	5.2	3.9	−81.2	6.9	5.2
Sub-sample 1[b]	8	5.0	−60.7	3.8	−9.5
1960.Q1–1973.Q4					
1960.Q3–1961.Q3	5	−2.7	−153.8	2.0	−47.3
1964.Q4–1966.Q2	7	2.9	−42.1	3.5	−9.8
1967.Q1–1967.Q4	4	2.9	−42.0	3.6	−7.0
1968.Q4–1972.Q3	16	4.7	−4.8	4.9	26.1
Sub-sample 2[b]	7	3.0	−101.7	9.6	19.9
1973.Q4–1989.Q4					
1973.Q4–1975.Q4	9	1.1	−63.8	15.1	56.8
1976.Q4–1977.Q4	5	−0.4	−111.7	9.2	−4.7
1979.Q1–1980.Q1	5	0.2	−93.3	10.6	9.8
1981.Q3–1983.Q2	9	−1.2	−138.1	11.3	17.6

[a]Computed as 100 × (cycle rate − subsample average rate) / subsample average rate.
[b]Period average.

later indicate that there was a break in the trend of both the output and inflation series.[2]

Table 1 indicates that Australia grew at an annual rate of about 4 percent in the last three decades. However, average growth slowed sometime in the early 1970s from 5 percent to around 3 percent. Over this period, Australia experienced eight recessions that on average lasted 7.5 quarters. Output growth fell an average of 81 percent below baseline during recessions. By way of comparison, the U.S. has experienced fewer recessions than Australia over a similar period (five). U.S. recessions on average are shorter (under four quarters) and steeper (output growth on average falls 170 percent below baseline during recessions) than Australia's. While these comparisons should be interpreted with some caution, because they partly reflect differences in how recessions are defined in each economy, they suggest contrasts in the cyclical behavior of Australian and U.S. output.[3]

According to Table 1 Australia's inflation averaged 6.9 percent over the sample period. Inflation rose over the two subsamples from 3.8 percent to 9.6 percent beginning in the mid-1970s. It is also apparent that on average there was no decline in inflation (in relation to baseline) during recessions in the second period.

Three factors are likely to have influenced cyclical output and inflation performance in Australia:

First, Australia meets most of its fossil fuel requirements through domestic production. In 1989, Australia produced 22.5 million metric tons of crude petroleum, about 86 percent of its domestic consumption. In 1989, fuels accounted for 5 percent of total imports, which to some degree were offset by exports.

Second, wage-setting is highly centralized due to the dominant influence of the Australian Council of Trade Unions. Nominal wages historically appear to have been relatively rigid. Australian unions were highly successful in putting upward pressure on wages until 1982. Some researchers argue (Chapman 1990) that wage restraint subsequently resulted from the Prices and Incomes Accord between the government and the unions signed in 1983, but others argue that the econometric evidence on this is weak (Blandy 1990).

Third, monetary policy appears to have played a largely passive role in curbing inflation and focused more on correcting external imbalances. The fiscal policy stance has fluctuated sharply over the sample period, on several occasions countercyclically. During the period of fixed exchange rates in place until December 1983, money growth and inflation are believed to have been influenced by external factors (like oil price shocks), as the rise in inflation in the 1970s mirrors similar increases in inflation in OECD countries. In contrast, after Australia switched to floating in December 1983, inflation on average has exceeded the OECD average. There is a widely held view that the government has sought to curb inflation largely through wage agreements under the Accord (Carmichael 1990, Stevens 1991). Monetary policy played a secondary, or even passive role in curbing inflation, but authorities appeared to favor monetary stimulus and nominal exchange rate depreciation to reduce current account deficits. Under these circumstances, the relationship between monetary policy and business cycle fluctuations would depend on the types of shocks accounting for current account deficits. If current account deficits were due to adverse movements in the terms of trade that would also tend to reduce domestic economic activity, monetary policy would operate countercyclically—that is, it would dampen business cycle fluctuations. However, if current account deficits were due to strong domestic demand stimulus, monetary policy would operate procyclically.

In contrast to the uncertain role of monetary policy in influencing business cycle behavior, fiscal policy appears to have operated countercyclically on a number of occasions. For example, the 1973.Q4–1975.Q4 recession was associated with a sharp increase in government consumption spending and a related rise in public borrowing to around 5 percent of GDP from 1 to 2 percent in the 1960s. The higher rate of borrowing was largely maintained until the early 1980s, when public sector borrowing rose to a peak of 7 percent of GDP at the time of the 1981–1983 recession. Large revenue increases and expenditure reductions subsequently reversed the upward trend in public sector borrowing, so that by 1988 the government was a net lender.

In Section IV, the preceding stylized facts are used to suggest interpretations of estimated responses to shocks in Australia.

[2]The sample is broken at the date closest to the break date reported in Table 3, subject to not splitting recessions across two samples. A similar criterion determines the break dates in the tables describing the cyclical behavior of inflation.

[3]Peak-to-trough dates for the U.S. are reported by the NBER, which currently tracks the behavior of four series to date recessions: real income, real sales, nonagricultural employment and industrial production. See Hall (1991). No comparable information is available for Australia, so peak-to-trough dates are those reported in OECD (1987). These peak-to-trough dates are based on the estimation of so-called phase-average trend (using the peaks and troughs of sine waves as the turning points of the cycle). It closely approximates a linearly deterministic trend if such a trend is unbroken, or a succession of segmented linear trends. The recession dates selected include what the OECD calls "minor cycles." In the absence of a more extensive dating procedure, the cycles reported in Table 1 are necessarily imprecise and the VAR analysis reported later provides additional information on whether they are reasonable.

II. The Model

Following Shapiro and Watson (1988), consider a standard growth model where shocks to demand are allowed to influence the behavior of output in the short run. In such a model, the log levels of the labor supply n_t^* and technology τ_t^* are governed by:

$$(1) \qquad n_t^* = \delta_n + n_{t-1}^* + \Theta_n(L)\epsilon_{2t}$$

$$(2) \qquad \tau_t^* = \delta_\varepsilon + \tau_{t-1}^* + \Theta_\varepsilon(L)\epsilon_{3t},$$

where ϵ_{2t}, ϵ_{3t} are mutually uncorrelated shocks that influence long-run growth (ϵ_{1t} is defined later), and $\theta_n(L)$, $\theta_\epsilon(L)$ are lag polynomials.[4]

The long-run log level of output is determined by a Cobb-Douglas production function:

$$(3) \qquad y_t^* = \alpha n_t^* + (1-\alpha)k_t^* + \tau_t^* .$$

Impose the theoretical restriction that the steady-state capital-output ratio is constant:

$$(4) \qquad k_t^* = y_t^* + \eta,$$

where η is the constant log capital-output ratio. Substituting (4) into (3) yields

$$(5) \qquad y_t^* = n_t^* + \left(\frac{1}{\alpha}\right)\tau_t^*,$$

where the constant term $\frac{\eta(1-\alpha)}{\alpha}$ is suppressed.

Equations (1) to (5) describe a real business cycle model with very simple dynamics. To close the model, introduce an aggregate demand shock ϵ_{4t} that is serially uncorrelated and uncorrelated with growth shocks ϵ_{2t}, ϵ_{3t}, and that allows the labor input and output to deviate temporarily from their long-run levels. Then we have

$$(6) \qquad n_t = n_t^* + \Xi_n(L)[\epsilon_{2t}\ \epsilon_{3t}\ \epsilon_{4t}]'$$

and

$$(7) \qquad y_t = y_t^* + \Xi_y(L)[\epsilon_{2t}\ \epsilon_{3t}\ \epsilon_{4t}]'.$$

It is assumed that labor supply and output are nonstationary. First-differencing to account for such nonstationarity, and substituting (1), (2), and (5) into (6) and (7), yields

$$(8) \qquad \Delta n_t = \Theta_n(L)\epsilon_{2t} + (1-L)\Xi_h(L)[\epsilon_{2t}\ \epsilon_{3t}\ \epsilon_{4t}]$$

$$(9) \qquad \Delta y_t = \Theta_n(L)\epsilon_{2t} + \alpha^{-1}\Theta_\varepsilon(L)\epsilon_{3t} + (1-L)\Xi_y(L)[\epsilon_{2t}\ \epsilon_{3t}\ \epsilon_{4t}].$$

In the present case, the model is completed by incorporating the processes governing the price level, p_t,

$$(10) \qquad \Delta p_t = \Xi_p(L)[\epsilon_{2t}\ \epsilon_{3t}\ \epsilon_{4t}].$$

The specification in equation (10) reflects the assumption that the price level is integrated (the first difference is stationary) and all the shocks have a long-run effect on the price level.

The model is now extended by including an exogenous oil price shock that has an effect on all of the other variables of the model,

$$(11) \qquad \Delta o_t = \Xi_o(L)\epsilon_{1t}.$$

To sum up, the model may be described as follows

$$(12) \qquad \begin{bmatrix} \Delta o_t \\ \Delta n_t \\ \Delta y_t \\ \Delta p_t \end{bmatrix} = B(L) \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \end{bmatrix}.$$

The shocks ϵ_{1t} to ϵ_{4t} respectively correspond to shocks to the oil price, labor supply, technology, and a demand shock.

In equation (12), shocks to the oil price are one source of external supply shocks. However, in a small open economy like Australia, other external disturbances may be important in influencing business cycle behavior. If external effects are important, both the supply and demand shocks in the present model may be interpreted as combinations of domestic and external shocks.

The structural shocks of model (12) can be recovered by first estimating a vector autoregression (VAR) model, and then exploiting the information from the sample variance-covariance matrix to achieve identification. As discussed earlier, one of the key identifying assumptions is that unobservable demand and supply shocks are identified by assuming that aggregate demand shocks have transitory effects while aggregate supply shocks have permanent effects on output. The estimation and identification procedures closely resemble those used by Shapiro and Watson (1988) and are discussed more fully in Appendix A.[5]

[4]These polynomials are assumed to have absolutely summable coefficients and roots outside the unit circle (i.e., the dynamics described by the polynomials are transitory, so the polynomials can be inverted).

[5]Although the model used in this paper is similar to Shapiro and Watson's (1988) model, the application differs in two ways: (i) the labor supply is represented by the labor force, rather than by the total hours worked by all employed persons; (ii) one equation is used to represent shocks to demand, rather than two equations, as in Shapiro and Watson. However, Shapiro and Watson do not separately identify the two demand shocks, but instead use the combined effects of the two shocks in their analysis.

III. DATA ANALYSIS

To estimate the system described by equation (12) I collected quarterly data for the oil price (o), the Australian labor force (n), Australian real GDP (y) and the Australian CPI (p). The data and sources are described in Appendix B. Certain properties of the series included in the model must be checked in order to determine the appropriate specification for estimation purposes. First, it is necessary to determine whether the series are difference- or trend- stationary. This is done by testing the null hypothesis that each series included in the model contains a unit root. If the variables are difference-stationary, it is appropriate to estimate the VAR model by using the first differences of the series. If the variables are trend stationary, the VAR model may be estimated by taking the residuals from a deterministic trend. Second, it is desirable to account for the possibility of breaks in the deterministic trend. The reason is that standard (Dickey-Fuller) tests may fail to reject the unit root null even if the time trend is deterministic, if there is a large one-time shift in the intercept or in the trend.[6] To account for this possibility, I test for breaks in the deterministic trend in each series. If the hypothesis of a trend break cannot be rejected, I test the unit root null against the alternative of a broken deterministic trend. Third, if the variables are difference stationary, it is necessary to establish whether the series in the model share common trends. If they do not, estimation of a VAR model in first differences is appropriate.

Unit Roots

To test for unit roots I apply the Augmented Dickey-Fuller and Phillips-Perron tests for unit roots to the levels and first differences of the series in the system (see Dickey and Fuller 1979, and Schwert 1987). The results of the tests, reported in Table 2, suggest that the labor force and output in Australia, as well as the oil price, are all difference-stationary. The results for the price level are ambiguous. Both tests indicate that the price level is nonstationary. However, when inflation is tested the Phillips test rejects the unit root null, whereas the Augmented Dickey-Fuller test cannot do so. In what follows, I assume that the price level is difference stationary.

The unit root test results should be interpreted with caution. Research has shown that tests for unit roots have low power (that is, they have low ability to reject the unit root null when it is false) against plausible local alternatives. Also, the autoregressive models and unit root test statistics computed for them have been found to be structurally unstable under small perturbations, so that small perturbations in the model lead to large changes in the distribution theory for the statistics (Cavanagh, undated).

Table 2

Tests for Unit Roots

Variable	Log Levels (with constant and trend)		First Differences (with constant)	
	Dickey-Fuller Test	Phillips	Dickey-Fuller Test	Phillips
Labor Force	−1.39	−1.75	−2.85*	−10.32***
Price (CPI)	−2.89	−2.36	−2.06	−7.83***
Real GDP	−1.92	−1.26	−4.39***	−12.34***
Oil	−1.54	−1.85	−3.55**	−6.65***

Note: * Reject null hypothesis (unit root) at 10% level.
** Reject null hypothesis at 5% level.
*** Reject null hypothesis at 1% level.
Seasonally adjusted data from 1960.Q1 to 1989.Q4, except for Labor Force, which is 1966.Q3–1989.Q4.

Trend Breaks

Standard tests for trend breaks assume that the date at which the break occurs is known without using the data series being tested. In practice, the data are used to find the break date, so standard critical values for testing the null hypothesis of no break in the trend cannot be used. To address this problem I follow a strategy similar to that adopted by Christiano (1992) and use a bootstrap methodology to calculate the most likely date for a break. As inspection of the series suggests that trend breaks occurred in the 1970s, I confine my search for breaks to that period. The test results, reported in Table 3, indicate that the null hypothesis of no trend break is rejected for GDP and CPI (the null of no trend break is not rejected for the oil price and the labor force, as these results are not reported here). On this basis, I test the unit root null hypothesis against the alternative of a deterministic trend with a break for GDP and CPI, also relying on bootstrap simulations to find the critical values. As also reported in Table 3, for these two series, the unit root null cannot be rejected against the alternative of a broken deterministic trend.[7]

[6]See Perron (1989) for the precise conditions.

[7]To construct Table 3, 1000 simulated series were generated using the following bootstrap methodology. The equation $\Delta y = \mu + \beta \Delta y$ was

Table 3

Tests for Break in Trend in the 1970s and for Unit Root Null against Alternative of Broken Deterministic Trend

Variable	Most Likely Break Date	Test for Break (*F* Statistic)	Test for Unit Root (*t* Statistic)
Real GDP	1974.Q2	332** (.03, 64.4)	−2.9 (.76, −3.5)
Price (CPI)	1974.Q2	523** (.03, 96.6)	−2.0 (.92, −3.2)

Note: See Notes to Table 2. Numbers in parentheses are significance levels and expected values.

Cointegration

While the preceding tests suggest that the model variables are nonstationary when considered individually, it is possible that these variables share a common nonstationary trend. In this case, a stationary linear combination of the variables may be found, and the variables are said to be *cointegrated*. When variables are cointegrated, estimating a VAR model where the series are expressed in first differences, as proposed above, would be inappropriate. One reason is that first-differencing would remove important information about the behavior of the variables contained in the common trend.[8]

A number of tests for cointegration have been developed in the literature. I use the method proposed by Johansen (1988) and applied by Johansen and Juselius (1990). Table 4 reports the results of the Johansen's trace and maximum eigenvalue tests. Based on the critical values reported by Johansen and Juselius (Table A.2) both tests fail to reject the null hypothesis that there is no cointegration. In what follows, I assume that the series in the model are not cointegrated and that estimation of the VAR model in first differences is appropriate.

To sum up, conventional tests suggest that all the series included in the model are difference stationary. There is evidence of a break in the deterministic trend in GDP and in the CPI, but the unit root null still cannot be rejected for these two series when this break is taken into account. Furthermore, a statistical test cannot reject the null hypothesis that there is no stationary linear combination of the variables in the model.

In view of the preceding results, the data are transformed as follows. The first differences of o, n, y and p were taken to obtain stationary representations. The differenced series Δo_t, Δn_t were demeaned by subtracting the respective sample means. To account for breaks in the trend rates

Table 4

Johansen Test for Cointegration

H_0: $r \leq$	0	1	2	3
Trace	44.5	22.1	9.8	2.2
95 % critical value	48.4	31.3	17.8	8.1
H_0: $r =$	0	1	2	3
Maximum eigenvalue	22.4	12.3	7.5	2.2
95% critical value	27.3	21.3	14.6	8.1

Note: Critical values are from Table A.2 of Johansen and Juselius (1990) which assumes that the nonstationary processes contain linear trends.

estimated. Disturbances were randomly drawn from the residuals of this equation with replacement and used to generate 1000 simulated series. The first sample observation was used as the starting value. To test for a trend break, equation $y_t = \alpha_0 + \alpha_1 d_t^b + \alpha_2 t + \alpha_3 sdum_t^b$ was then re-estimated using each of the 1000 artificial series for $b = bdat + 5$ to $b = ldat$. The maximum F statistic for b between 1970:Q1 and 1979:Q4 for each of the 1000 artificial series was selected. These 1000 maximum F-statistics were then ranked in ascending order. The 1 percent critical value was then given by the F statistic with rank 990 (1 percent of the set of maximum F statistics exceed this F-value), the 5 percent critical value by the statistic with rank 950, and so on. The expected value is given by the statistic with rank 500.

To test the unit root null against the alternative of a broken deterministic trend, the equation $\Delta y_t = \beta_0 + \beta_1 d_t^b + \beta_2 t + \beta_3 d_t^b + \beta_4 y_{t-1} + \beta_5 \Delta y_{t-1} + \beta_6 \Delta y_{t-2}$ was reestimated using each of the 1000 artificial series used to generate Table 3. For each series, the date b was set to correspond to the peak of the F statistic computed by the equation used to find the most likely trend break in Table 3. To find critical values, the 1000 t-statistics testing the null were collected, and critical values were constructed in a manner analogous to Table 3.

[8]Engle and Granger (1987) show that the appropriate model if the variables are cointegrated is an error correction model, rather than a VAR in first differences. Another way of looking at this problem is to note that a VAR made up of first-differenced variables that are cointegrated involves "overdifferencing." As in the univariate case of "overdifferencing," the vector ARMA system of variables expressed in first differences will contain noninvertible MA terms that cannot be represented by a VAR.

of growth and inflation, the differenced series Δy, Δp were demeaned by subtracting the appropriate subsample means, where the subsamples were defined by the break dates identified using the bootstrap simulation procedure (1974.Q2 in both cases). The demeaned series were used to estimate a VAR model. (A similar procedure of subtracting subsample means is used by Blanchard and Quah. However, they pick the break date without using a statistical test.)

IV. Model Estimation Results

The VAR model was estimated over 1966.Q3–1989.Q4 (no earlier data are available for the Australian labor force). Using the identifying restrictions discussed in Appendix A, a structural moving average representation (as in equation (12)) was obtained. This moving average representation allows us to address the three questions posed in the introduction to this paper.

Impulse Responses

The first question posed in the introduction, concerning the qualitative responses to supply and demand shocks, can be addressed by reference to Charts C.1 to C.4 in Appendix C, which illustrate the effects of one standard deviation shocks to the levels of the variables. (By construction, shocks to the domestic variables have no effect on the oil price, so the response of the oil price to Australian variables is not illustrated.) The impulse responses are illustrated for horizons up to 12 quarters to focus on the short-run dynamics. In general, the impulse responses are close to the long-run values at these horizons. Also, the one standard error bands around the impulse responses in a number of cases widen sharply at long forecast horizons, as might be expected for nonstationary series.[9] For these reasons, the loss of information from truncating the impulse response horizons is not very great.

An important test of the plausibility of the model and identifying procedure adopted in this paper is whether the responses to supply and demand shocks conform to the predictions of theory. We would expect

- positive shocks to the oil price to reduce output and increase the price level in the long-run;
- positive shocks to labor supply and technology to increase output and reduce the price level in the long-run;
- positive shocks to demand to increase labor and output temporarily (as a result of the identifying restrictions) and the price level permanently;

The charts indicate that the responses to shocks in the model broadly conform to these expectations, although the standard error bands are in some cases quite wide, particularly at horizons exceeding four quarters.

The charts also reveal some interesting dynamics: for example, GDP rises sharply in response to technology shock, overshoots its long-run level slightly at about 10 quarters before settling to close to its long-run level of around ¾ percent above the pre-shock level. This long-run level is achieved at around 20 quarters and is not shown in the chart. (The CPI declines with similar, but smoother, dynamics.) In contrast, Blanchard and Quah (1989), Shapiro and Watson (1988) and Moreno (1992a) indicate a more pronounced overshooting in the output response to technology shocks in the U.S. and Japan respectively. However, these comparisons should be interpreted with caution because the standard errors in all these models appear to be quite large.

In addition, some of the impulse response results appear to be broadly consistent with the characteristics of the Australian economy discussed in Section I:

Australia does not appear to be vulnerable to oil price shocks in the very short run, which is consistent with its status as oil producer and exporter. The impulse responses indicate that Australian GDP *rises* temporarily in response to oil price shocks, followed by a long-run decline. This suggests that an oil price increase initially stimulates the economy through Australia's oil sector, but the stimulus is reversed as the effects of a higher oil price spread to the rest of the economy.

The effects of demand shocks on output die out quickly, which is consistent with an active countercyclical policy The charts indicate that the effects of a positive shock to GDP are fully reversed within one year, which appears to be relatively fast. In contrast, Blanchard and Quah (1989) find that the effects of a demand shock on U.S. output take about six years to be fully reversed. Moreno (1992a) estimates that in Japan, the effects of a demand shock on output are fully reversed after two years. The rapid reversal of demand shocks suggests that the countercyclical effects of fiscal policy and (to the extent applicable) of monetary policy were quite important in Australia (recall discussion in Section I). However, it is important to stress that the

[9] These standard error bands are obtained by using a Monte Carlo simulation procedure with 300 replications to construct pseudo-impulse responses and the first and second moments of these impulses. The pseudo-impulse responses are generated by using draws from the Normal and Wishart distributions to modify the variance covariance matrix and the moving average coefficients of the structural innovations. See Doan (1990). In the charts, a two-standard-error band tends to disguise the short-run dynamics in the impulse responses, so a one-standard-error band is shown instead.

rapid reversal in the effects of demand shocks on output is only an indicator of the possible effects of countercyclical policy, and that other explanations for this rapid reversal may be offered. In the model estimated in this paper, demand shocks reflect the combined effects of private and public demand, and there is no way of separating these two effects.

Australia appears to have a relatively flat short-run Phillips curve, which is consistent with apparent rigidities in the labor market. To assess the Phillips curve tradeoff, I computed the ratio of cumulative GDP growth per unit of cumulative inflation in response to a one-standard-deviation shock to demand.

A shock to demand yields its greatest output growth stimulus per unit of inflation in the first quarter, about 208 percent. The cumulative output gain subsequently tapers off smoothly to 147.50 percent in the second quarter, 100 percent in the third quarter, and to 48 percent in the fourth quarter. The cumulative output gain is negative and small at eight and twenty quarters, and is zero at forty quarters. To provide a benchmark, these results may be compared to estimates obtained from a similar model for Japan (Moreno 1992a) where labor markets appear to be more flexible than in Australia. In Japan, the corresponding cumulative increases in output growth per unit of inflation are 93 percent at one quarter, 43 percent at four quarters, 3 percent at eight quarters, and close to zero at twenty quarters. Thus, Australia appears to have a relatively favorable output-inflation tradeoff in the very short run.

Variance Decompositions and the Importance of Supply Shocks

The impulse response functions illustrate the qualitative responses of the variables in the system to shocks to supply and demand. To indicate the relative importance of these shocks requires a variance decomposition. In order do this, consider the n-step ahead forecast of a variable based on information at time t. The variance of the error associated with such a forecast can be attributed to unforecastable shocks (or innovations) to each of the variables comprising the system that occur between $t+1$ to $t+n$.

Table 5 reports the variance decompositions of the structural forecast errors of the variables in levels, at horizons up to forty quarters (10 years).

By construction, the variance in the forecast error of the oil price is attributable entirely to shocks to the oil price and is not reported. It is also apparent that shocks to the labor supply are the main determinants of the variance of the forecast error of the labor force at all horizons. This result would probably differ if a variable that is more sensitive to changes in demand in the short-run were used.

We can use the variance decompositions for GDP to assess the empirical importance of demand and supply shocks, which is the second question posed in the introduction. Demand shocks are most important in the very short run, accounting for 64 percent of the forecast error one-quarter ahead. However, supply shocks soon assume the dominant role: They account for 74 percent of the forecast error variance at eight quarters and 95 percent at forty quarters. Supply shocks are in turn dominated by shocks to technology.

Three points are worth highlighting. First, the variance decomposition estimates are relatively imprecise, so the results of the point estimates should be viewed with some caution. For example, at the one-quarter horizon for demand shocks, the 95 percent confidence band ranges from a low of 27 percent to a high of 89 percent.[10] However, the estimates in Table 5 do not appear to be less precise than estimates reported by Blanchard and Quah (1989) or Shapiro and Watson (1988), or the estimates in Sims's (1980) study (see Runkle (1987)).

Second, in their study of the U.S. economy, Shapiro and Watson (1988) found that shocks to labor supply were large at short horizons (in the neighborhood of 40 percent or higher). This is surprising because theory and empirical studies of the U.S. economy suggest an important role for permanent shocks to labor supply at long forecast horizons, but not at short ones. In the case of Australia, the contribution of labor supply shocks to the variance of the forecast error is small. It ranges from 4.5 percent at one quarter to 13 percent at eight quarters and down to 5 percent at forty quarters. One possible explanation for the relatively small contribution of the labor supply is that the

[10]The empirical 95 percent confidence band was constructed by using a bootstrap simulation procedure with 300 replications to generate pseudo-variance decompositions, as was done for the impulse responses. However, instead of constructing a symmetric one-standard-error band based on the normal approximation, I define the 95 percent band as follows. The lower bound is that value such that 2.5 percent of the pseudo-variance decomposition values are lower. The upper bound is that value such that 2.5 percent of such values are higher. One advantage of this approach is that it excludes values below 0 or above 100 and thus reflects the constraint that the variance decompositions must sum to 100. The empirical distribution found in this manner is skewed, as the point estimate of the variance decomposition in a number of cases is close to the upper or lower boundary of the 95 percent band. A similar bootstrap procedure is used by Blanchard and Quah (1989) to report asymmetric empirical one-standard-error bands. Shapiro and Watson (1988) report one-standard-error bands that appear to be based on the normal approximation. The normal approximation does not take into account the constraints on the values of the variance decompositions, so the lower bound of the standard error band may be negative, and the upper bound may exceed 100. See Runkle (1987) for a discussion of some of these issues.

Table 5
Variance Decompositions

Quarters Ahead	Proportion of Variance Explained by Shock to: Aggregate Supply				Aggregate Demand
	Oil Price	Labor Supply	Technology	Total	
Labor Force					
1	0.7 (0.0,12.8)	87.2 (48.0,96.3)	11.7 (0.2,37.6)	99.6	0.4 (0.0,20.7)
4	1.8 (0.7,14.7)	83.4 (47.9,87.3)	13.7 (6.2,30.9)	98.9	1.1 (0.4,15.9)
8	1.2 (0.9,14.2)	88.8 (58.9,90.4)	7.2 (3.6,21.2)	97.2	2.8 (1.6,15.2)
12	0.8 (0.9,12.9)	92.7 (58.2,92.9)	4.7 (2.6,23.1)	98.2	1.8 (1.1,16.7)
20	0.6 (0.7,12.5)	95.4 (44.8,95.7)	2.9 (1.7,26.2)	98.9	1.1 (0.7,22.0)
40	0.4 (0.5,16.1)	97.5 (6.1,97.7)	1.5 (0.9,49.6)	99.4	0.5 (0.3,43.5)
GDP					
1	2.2 (0.0,19.8)	4.5 (0.1,16.1)	29.6 (3.2,61.7)	36.3	63.6 (26.7,89.4)
4	1.9 (0.7,20.1)	10.0 (1.3,29.7)	39.6 (16.9,60.1)	51.5	48.5 (24.3,66.3)
8	2.2 (1.9,26.6)	12.9 (2.6,37.9)	58.4 (26.8,69.0)	73.5	26.5 (12.7,43.7)
12	3.7 (2.2,32.4)	9.7 (2.1,36.0)	69.7 (26.9,76.1)	83.1	16.9 (7.5,42.7)
20	5.7 (2.0,42.4)	6.8 (1.6,32.0)	77.1 (23.4,81.1)	89.6	10.4 (4.0,47.9)
40	6.6 (1.2,49.0)	5.0 (0.7,33.0)	83.0 (18.8,88.5)	94.6	5.4 (1.7,47.5)
CPI					
1	0.6 (0.0,14.3)	11.6 (1.0,26.8)	62.5 (45.9,73.3)	74.7	25.4 (16.4,33.5)
4	1.5 (0.1,19.8)	15.2 (1.2,36.7)	61.4 (37.4,77.2)	78.1	21.8 (7.3,39.9)
8	5.7 (0.2,37.4)	6.3 (1.0,29.1)	60.4 (30.8,78.7)	72.4	27.6 (7.3,51.1)
12	9.2 (0.3,46.6)	3.3 (0.6,23.9)	58.0 (24.5,78.3)	70.5	29.4 (5.9,52.3)
20	12.2 (0.2,54.6)	1.8 (0.4,27.5)	55.4 (19.8,76.4)	69.4	30.6 (4.9,57.1)
40	13.6 (0.1,61.1)	0.8 (0.2,28.1)	54.4 (17.0,77.5)	68.7	31.2 (4.5,60.2)

Note: Empirical 95 percent confidence bands are in parentheses.

proxy used for this variable, the labor force, varies relatively little. If total employment—which varies somewhat more than the labor force—is used instead of the labor force in the model, labor supply shocks are larger but still small. They account for 2 percent of the variance of the forecast error at one quarter, 28 percent at eight quarters and 29 percent at forty quarters.[11]

Third, oil price shocks play a limited role, accounting for about 2 percent of the variance of the forecast error up to eight quarters, rising to under 7 percent at forty quarters. This is somewhat below the short-run results for the U.S. obtained by Shapiro and Watson (1988) but similar to their long-run results.

Supply shocks are the most important factor influencing the short-run behavior of the price level in Australia. Supply shocks account for 75 percent of the variance of the one-quarter-ahead forecast error of Australia's CPI, rising to 78 percent at four quarters, and then falling gradually to 69 percent at forty quarters. Technology shocks are the main source of supply shocks at all horizons. Shocks to labor supply have a stronger influence at short horizons (fewer than twenty quarters), accounting for up to 15 percent. Oil price shocks have a larger influence at longer horizons (twenty to forty quarters), accounting for about 12 to 14 percent. The oil price has a stronger influence on the price level than on GDP.

To sum up, both demand and supply shocks have an important effect on output throughout the Australian business cycle. Demand shocks are dominant in the very short-run, but their importance tapers off quickly as the forecast horizon is extended. In contrast, supply shocks have a dominant influence on the price level at all forecast horizons.

Evidence from Other Studies

The preceding results may be compared to Shapiro and Watson's (1988) results for the U.S. using a similar model. The contribution of supply shocks to output in the U.S. is 72 percent at a quarter's horizon and 80 percent at eight quarters, which is larger than the 36 percent and 74 percent found for Australia in Table 5. However, supply shocks explain 12 percent or less of the variance of the U.S. price level at horizons up to eight quarters, much lower than the 78 percent found for Australia over similar horizons.[12]

The results of a study of Scandinavian business cycles by Gerlach and Klock (1990), which covers Denmark, Norway and Sweden, are closer to those reported here. Gerlach and Klock estimate a bivariate model of output and price for each economy using annual data for the period 1950–1988, and impose the identifying restrictions proposed by Blanchard and Quah (1989). In general, they find that the contribution of supply shocks to output for all three countries at a year's horizon is large, ranging from 50 to 75 percent. The contribution to inflation in two of the three countries is also large, ranging from 66 percent to 83 percent.[13]

Patterns of Cyclical Behavior

Further insights on cyclical behavior can be gained by examining the pattern of shocks to output during cyclical downturns, which is the third question posed in the introduction. For this purpose, Chart 1 reports the eight-step ahead forecast error in output growth and the cumulative contributions of demand and supply shocks to this error in Australia. Australia's VAR sample begins in 1966.Q3 (the starting date for the labor force series) and data points are used up in setting an eight-quarter forecast horizon. As a result, Chart 1 begins in 1970 and only five of the eight recessions reported in Table 1 are included.

The description of recessions offered in Chart 1 differs from that offered in Table 1. In Table 1, the severity of recessions is measured in terms of deviations from a baseline rate of growth. In Chart 1, the severity of recessions is assessed by examining how unforecastable innovations make output growth deviate from what was anticipated given the information available eight quarters before.

It is apparent that the first recession indicated in the chart (which actually begins in 1968.Q4, according to Table 1) is not considered a recession by the VAR model:

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[11]Shapiro and Watson (1988) use total hours worked by all workers, which varies even more at business cycle frequencies. Judd and Trehan (1989) point out that total hours appears to contain a very strong demand component, so using it as a proxy for labor supply can result in implausible dynamic responses to shocks.

[12]Previous studies on the relative importance of supply shocks based on U.S. data reveal that the estimates are very sensitive to assumptions about trend behavior, such as whether the series are trend or difference stationary, or whether there are breaks in the mean rate of drift of output. For this reason, the present study has attempted to ensure that the assumptions about trend behavior are reasonable, by testing for unit roots, trend breaks and cointegration. Also, the comparison with the U.S. is based on a study which makes very similar assumptions to those adopted in this paper.

[13]In *Denmark* at a year's horizon, supply shocks account for around 50 percent of the variance of output and around two-thirds of the variance of inflation. At a five-year horizon, the proportion rises to 75 percent for output and to 35 percent for inflation. In *Norway* supply shocks account for around 98 percent of the variance of output at all horizons, but for just over 10 percent of the variance of inflation. Finally, in *Sweden* at a year's horizon, supply shocks account for 60 percent of the variance of output and 83 percent of the variance of inflation. At a five-year horizon the proportion rises to 95 percent for output and falls to 80 percent for inflation.

The forecast errors tend to be positive rather than negative.[14] For the remaining four recessions, the forecast errors are consistently negative, as expected. The discussion that follows focuses on these last four recessions.

The following features of Australian recessions stand out. First, negative supply and demand shocks have been a feature of the four recessions discussed here. Second, the recessions of 1973.Q4–1975.Q4 and of 1981.Q3–1983.Q2 were more severe than the two intervening recessions (1976.Q4–1977.Q4 and 1979.Q1–1980.Q1). The two more severe recessions were associated with larger adverse supply shocks.

Chart 2 illustrates the eight-step ahead forecast error for inflation in Australia as well as the cumulative contributions of supply and demand shocks to the forecast error. It is apparent that recessionary episodes in Australia have been associated with adverse supply shocks that have contributed to temporary increases in inflation. With the exception of the 1982 recession, these inflationary pressures were reinforced by shocks to demand.

V. *Summary and Conclusions*

This paper has estimated a small structural vector autoregression model to assess the determinants of business cycle behavior in Australia. The model sheds light on the dynamic responses of Australian macroeconomic variables to demand and supply shocks. In the model, shocks to technology raise output and lower the price level, while shocks to demand temporarily raise output and permanently raise the price level. These responses conform to intuition and theoretical expectations.

The empirical results also shed light on the relative importance of demand and supply shocks in influencing output and inflation behavior in Australia. Demand shocks are dominant in determining fluctuations in Australian output at a one quarter horizon, but supply shocks assume the larger role at longer horizons. Supply shocks also account for most of the fluctuations in the Australian price level. In contrast, research by Shapiro and Watson (1988), using a similar model, finds that supply shocks play a larger short-run role in influencing U.S. output and a very small role in influencing the U.S. price level. The empirical results also indicate that supply shocks in Australia are dominated by shocks to technology, with shocks to the labor supply or to the oil price playing a smaller role.

[14]For this episode, the VAR results appears to conform more closely to the views of informed observers than does Table 1. In private correspondence, Glenn Stevens of the Reserve Bank of Australia indicates that 1968 is generally not regarded as a recession year in Australia.

CHART 1
Components of Output Growth Forecast Error (8 steps)

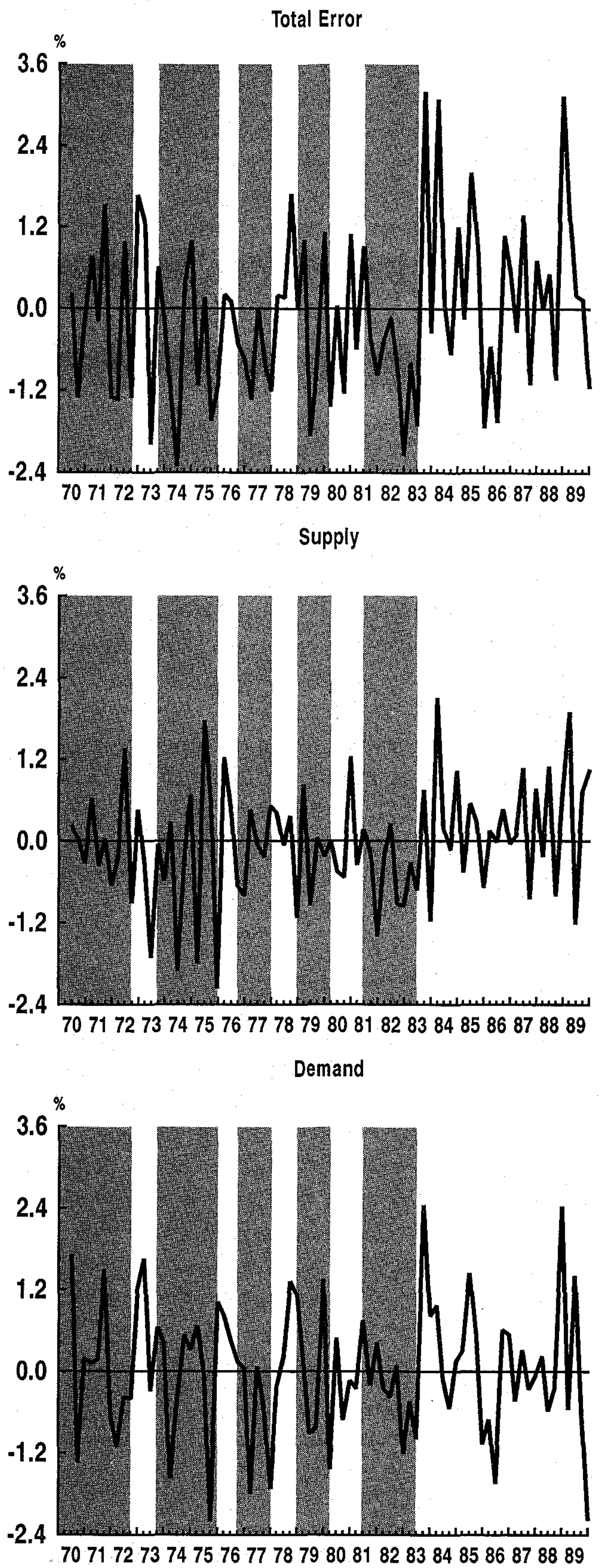
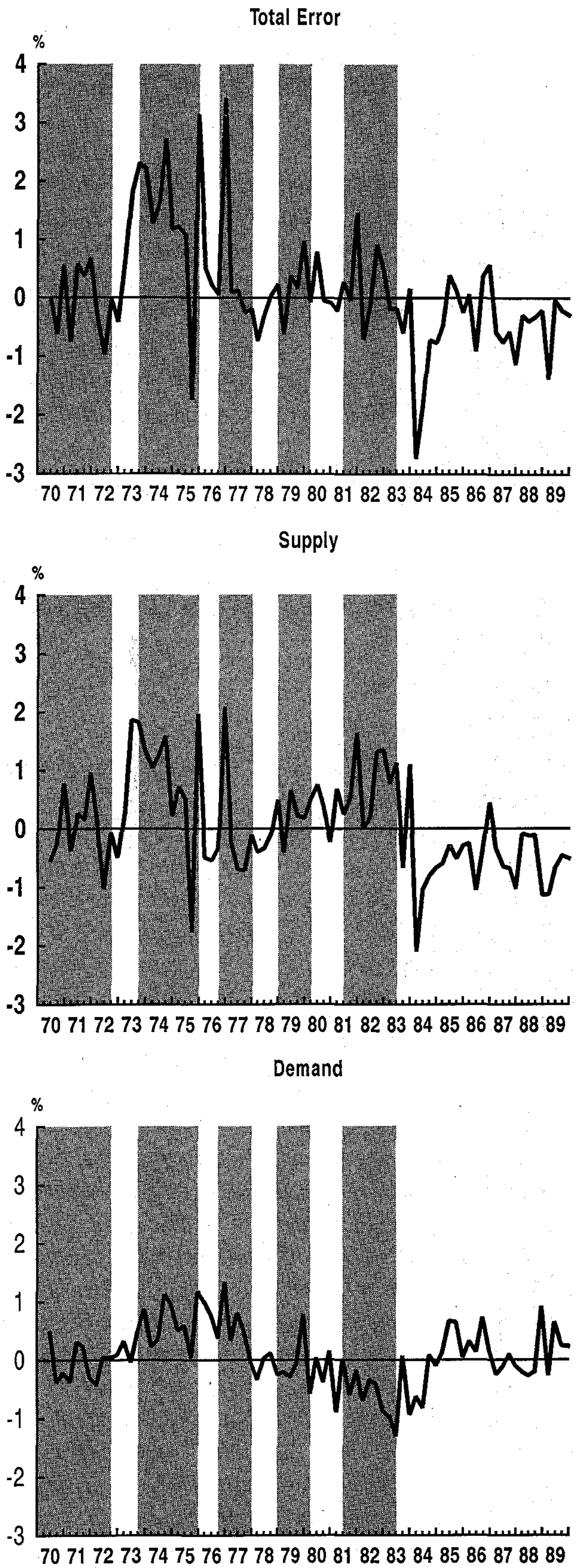


CHART 2
Components of Inflation Forecast Error (8 steps)



The present paper has used a model that has certain appealing theoretical features and has the further advantage of being directly comparable to Shapiro and Watson's (1988) model of the U.S. However, future research can extend the model in several ways. First, demand shocks identified in this paper reflect the combined impact of private and government actions, and can therefore only provide indirect insights on the possible role of government policy in influencing business cycle fluctuations. A larger model that explicitly identifies monetary and fiscal policy shocks could be used to analyze the role of government policy in Australia more directly. Second, other variables, such as wages and hours worked, may be introduced to capture the effects of labor markets more fully. Third, the model could be extended to assess the impact of external shocks in addition to the oil price. Aside from clarifying the relative importance of external and domestic shocks, such an extension could potentially shed light on a number of interesting questions, such as the insulation properties of alternative exchange rate regimes.[15]

[15]Moreno (1992b) assesses insulation under alternative exchange rate regimes in Korea and Taiwan.

Appendix A
Identifying VARS

Moving Average Representation[1]

To motivate the general approach to setting up and identifying VAR models, consider a $k \times 1$ vector of endogenous variables z, with a structural moving average representation given by:

$$z_t = B(L)\epsilon_t \tag{A.1}$$

where

$B(L) = B_0 + B_1L + B_2L^2 + \ldots$ is a $k \times k$ matrix of polynomials in the lag operator L

ϵ_t is a $k \times 1$ vector of white noise disturbance terms

$\epsilon_t \sim (0, \Sigma_\epsilon)$ and Σ_ϵ is diagonal (that is, the structural shocks are mutually orthogonal)

In order to estimate the response of the elements of z_t to innovations in the elements of the mutually orthogonal structural disturbances contained in ϵ_t, a procedure is needed to identify these structural disturbances. The conventional approach is to estimate the VAR representation of z_t:

$$H(L)z_t = u_t, \tag{A.2}$$

where

$H(0) = I$ (that is, no contemporaneous variables enter on the right hand side of the VAR equations)

$u_t \sim (0, \Sigma_u)$, where Σ_u is not a diagonal matrix (that is, the residuals are not mutually orthogonal)

If we invert the VAR representation, we obtain,

$$z_t = D(L)u_t; D(L) = H(L)^{-1}. \tag{A.3}$$

By decomposing the elements of (A.3) using the matrix $B(0)$ (the matrix that defines the contemporaneous structural relations) between the variables, we can recover (A.1):

$$D(L)u_t = D(L)B(0)B(0)^{-1}u_t = B(L)\epsilon_t \tag{A.4}$$

so we can write

$$D(L) = B(L)B(0)^{-1} \tag{A.5}$$

and

$$u_t = B(0)\epsilon_t \tag{A.6}$$

[1]This section draws heavily on the lucid discussion in Hutchison and Walsh (1992).

Equation (A.6) indicates that an estimate of $B(0)$ is needed in order to recover the mutually orthogonal structural disturbances ϵ_t from the estimated VAR residuals u_t.

To motivate the conditions such an estimate must fulfill, note that (A.6) also implies that the diagonal covariance matrix of structural disturbances Σ_ϵ is related to the covariance matrix of the VAR residuals, Σ_u, by

$$\Sigma_\epsilon = B(0)^{-1}\Sigma_u B(0)'^{-1}. \tag{A.7}$$

Equation (A.7) suggests that two conditions must be satisfied in order to identify $B(0)$. First, the number of parameters to be estimated must not exceed the number of unique elements in the sample covariance matrix Σ_u. Specifically, there are k^2 unknown elements in $B(0)$, and the matrix Σ_u contains $k(k+1)/2$ unique elements. A necessary condition for identification is that $k^2 - k(k+1)/2 = k(k-1)/2$ additional restrictions be imposed. We can think of this as an order condition.

Second, the system of nonlinear equations resulting from (A.7) must have at least one solution. This may fail if identifying restrictions are imposed in a manner that prevents equating elements on both sides of the equation. Bernanke (1986) suggests that this can be thought of as a rank condition.

Identification

A number of approaches to identification of a VAR system have been adopted in the literature. The earliest approach, pioneered by Sims (1980), assumes that $B(0)$ is lower triangular. This imposes restrictions on the contemporaneous correlations of shocks to variables that are equivalent to assuming that the economy described by the vector z_t has a recursive structure. Under such a structure, the first variable is unaffected by shocks to the remaining variables, the second variable is affected by shocks to the first two variables, but is unaffected by shocks to the remaining variables, and so on. (The last variable is affected by shocks to all variables.

The main disadvantage of Sims's approach is that it is not easily reconciled with economic theory. Two alternative approaches have been adopted to address this problem. First, a number of authors (Bernanke 1986, Sims 1986, Walsh 1987, Blanchard 1989) have imposed zero restrictions on $B(0)$ to achieve identification. Such contemporaneous restrictions are explicitly motivated by theory and do not necessarily assume a recursive structure.

Second, other researchers (Blanchard and Quah 1989, Shapiro and Watson 1988, Judd and Trehan 1989, 1990, Hutchison, Walsh 1992 and Moreno 1992a) have achieved identification by imposing zero restrictions on the long-run multipliers $B(1)$, in a manner that permits the estimation of

B(0). Such restrictions are motivated by the idea that certain disturbances have no long-run impact on certain elements of z.

Setting $L=1$, (A.4) implies that

$$B(0) = D(1)^{-1}B(1) = H(1)B(1) \tag{A.4'}$$

where $D(1)$ is the matrix of long-run multipliers estimated from the VAR and $H(1)$ is the matrix of sums of coefficients obtained from the estimated VAR. Restrictions on $B(1)$, along with the restrictions implied by (A.6), can be used to obtain an estimate of $B(0)$. For higher order VARs, higher order polynomials are involved in finding a solution, so numerical techniques are needed to estimate $B(0)$. One such technique is applied by Hutchison and Walsh (1992).

Estimation

A simple method for recovering the structural disturbances is applied by Shapiro and Watson (1988) in a recent study of the U.S. economy. Shapiro and Watson estimate a system that yields the structural disturbances directly from the VAR representation, that is,

$$C(L)z_t = \epsilon_t, \tag{A.8}$$

where $C(L) = B(L)^{-1}$, and $B(L)$ is found in (A.1) or (12) in the text.

The structural disturbances are recovered directly from (A.8) as follows. First, $C(0) \neq I$ so contemporaneous values of z_t are now allowed to enter on the right hand side of some of the equations. To obtain consistent estimates, these equations are estimated using two-stage least squares, with the exogenous and the predetermined (lagged) variables as instruments.

Second, the dynamic restrictions on the long-run multipliers (zeros on $B(1)$) are reflected in restrictions on the sums of coefficients of the appropriate variables (that is, as zeros on the corresponding elements of $C(1)$).

Third, Shapiro and Watson ensure that the estimated residuals are mutually orthogonal by estimating each equation in (A.8) sequentially and including the residuals from previous equations in the estimate of the current equation. Thus, the residual in the first equation is used in estimating the second equation, the residuals of the first two equations are used in estimating the third equation, and so on.

Another way to ensure that the appropriate residuals are mutually orthogonal is to estimate each equation in (A.8) without including residuals from the other equations and then use the Choleski decomposition of the covariance matrix to obtain the moving average representation. Although the Choleski decomposition is used, the system is not in this case recursive, because the contemporaneous values of z_t have been included in estimation. (Thus, the critique of atheoretical recursive methods of VAR identification does not apply here.)

This paper uses Shapiro and Watson's (1988) estimation technique to recover structural shocks from a VAR system but relies on the Choleski decomposition to recover orthogonal shocks.

To achieve identification, I impose the following restrictions: First, the oil price depends only on its own lagged values and is completely unaffected by other variables in the model. Second, the labor force can be affected by other variables in the short run; however, the long-run impact of these other variables is zero (in particular, there are no wealth effects on the labor supply). Third, the level of GDP is permanently affected by shocks to the oil price, the labor supply, and technology (supply shocks). Shocks to demand have temporary effects on GDP. No restrictions (except the lag length) are imposed on the effects of the variables of the system on the price level. Given such restrictions, the long-run multipliers in equation (12) in the text satisfy[2]:

$$B(1) = \begin{bmatrix} b(1)_{11} & 0 & 0 & 0 \\ 0 & b(1)_{22} & 0 & 0 \\ b(1)_{31} & b(1)_{32} & b(1)_{33} & 0 \\ b(1)_{41} & b(1)_{42} & b(1)_{43} & b(1)_{44} \end{bmatrix} \tag{A.9}$$

The zeros in the first and second rows reflect the restriction that oil prices and the labor supply are unaffected by other variables in the long run. The zero in the third row reflects the restriction that the demand shock, ϵ_{4t} in equation (12) of the text, has only temporary effects on output. In a 4-equation system, the variance covariance matrix contains 10 unique elements, but there are 16 unknown parameters. Six additional restrictions are needed to identify the system. In equation (A.9), there are seven restrictions, implying that the system is overidentified.

To impose the identifying restrictions discussed previously, the following equations are estimated:

$$\Delta o_t = \sum_{i=1}^{l} \Delta h_{11,i} o_{t-i} + u_{1t} \tag{A.10}$$

[2]For a matrix of polynomials in the lag operator $B(L) = B_0 + B_1L + B_2L^2 + \ldots$, the matrix of long-run multipliers is found by setting $L=1$. This yields $B(1) = B_0 + B_1 + B_2 + \ldots$ or the sum of the moving average coefficients.

$$\text{(A.11)}\quad \Delta n_t = \sum_{i=0}^{l-1} \Delta^2 h_{21,\,i} o_{t-i} + \sum_{i=1}^{l} h_{22,\,i} \Delta n_{t-i} + \sum_{i=0}^{l-1} h_{23,\,i} \Delta^2 y_{t-i} + \sum_{i=0}^{l-1} h_{24,\,i} \Delta^2 p_{t-i} + u_{2t}$$

$$\text{(A.12)}\quad \Delta y_t = \sum_{i=0}^{l} h_{31,\,i} \Delta o_{t-i} \quad \sum_{i=1}^{l} \Delta h_{32,\,i} n_{t-i} + \sum_{i=1}^{l} h_{33,\,i} \Delta y_{t-i} + \sum_{i=0}^{l-1} h_{34,\,i} \Delta^2 p_{t-i} + u_{3t}$$

$$\text{(A.13)}\quad \Delta p_t = \sum_{i=0}^{l} h_{41,\,i} \Delta o_{t-i} + \sum_{i=1}^{l} \Delta h_{42,\,i} n_{t-i} + \sum_{i=1}^{l} h_{43,\,i} \Delta y_{t-i} + \sum_{i=1}^{l} h_{44,\,i} \Delta p_{t-i} + u_{4t}$$

where it is assumed that o, n, y and p are difference stationary, and a lag length of five is used in all equations. Using this lag length yields Q statistics that do not reject white noise at the 5 percent marginal significance level in all equations.

Equations (A.10) and (A.13) are estimated by OLS. Equations (A.11) and (A.12) are estimated by two-stage least squares, with the contemporaneous value of the oil price and the lagged values of all variables as instruments. In equations (A.11) and (A.12), the restriction that certain variables have zero effects in the long run is imposed by expressing these variables in second differences and setting the maximum number of lags to four for these equations.

The system (A.10) to (A.13) incorporates several of the restrictions implied by (A.9). However, the system does not exactly correspond to (A.8) because the variance covariance matrix of the system (A.10) to (A.13) is not diagonal. That is, the unadjusted residuals u_{1t}, u_{2t}, u_{3t}, u_{4t}, are correlated and are not (necessarily) the same as the uncorrelated structural disturbances in (A.8) or in the moving average representation of (12) in the text. To identify the three supply disturbances ϵ_{1t}, ϵ_{2t}, ϵ_{3t}, and the demand disturbance ϵ_{4t} in equation (12) in the text, I select a lower-triangular matrix G such that $G^{-1}\Sigma_u G'^{-1} = I$, where Σ_u is the variance-covariance matrix of the system (A.10) to (A.13). With such a matrix G, it is possible to define $\epsilon_t = u_t G^{-1}$ and $E\epsilon_t \epsilon_t' = I$.

In typical applications, the use of a lower-triangular matrix G, also known as the Choleski factorization, yields a recursive system of mutually orthogonal disturbances of the type proposed by Sims (1980). In the early VAR literature, this was the sole basis for identification. Since many theoretical models do not imply a recursive economic structure, it is difficult to rely on this approach alone to distinguish between demand and supply shocks.[3]

In the present case, however, the Choleski decomposition is only *one* element of the identification procedure, designed to extract mutually orthogonal disturbances. Identification also depends on the specification of the VAR equations, which incorporate the restrictions proposed by Blanchard and Quah and satisfy (A.9) (the Choleski factorization alone cannot guarantee that equation (A.9) will be satisfied). It may also be noted that since contemporaneous values of the explanatory variables are included in the VAR model, the resulting structure of the economy is *not* recursive.

Appendix B
Data Description and Sources

Australia, quarterly

Real Gross Domestic Product. Millions of 1984–85 Australian dollars (A$), seasonally adjusted.
Source: OECD *Main Economic Indicators.*

Consumer Price Index. 1985 = 100.
Source: *International Financial Statistics*, International Monetary Fund.

Labor Force. Total labor force, thousands of persons.
Source: Reserve Bank of Australia, *Australia Reserve Bulletin.*

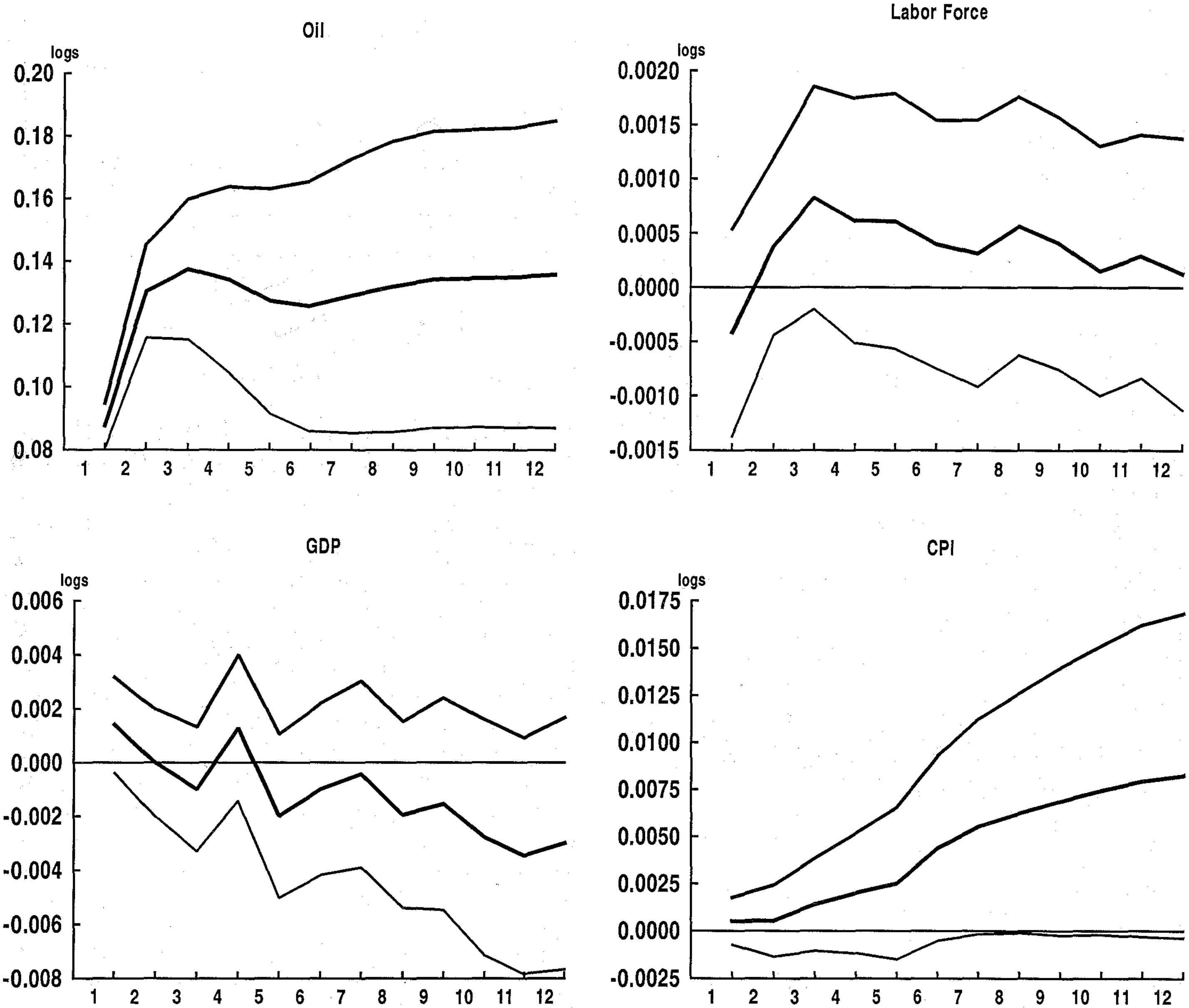
International

Oil. Crude petroleum component of U.S. PPI, 1982 = 100, quarterly average of monthly data.
Source: Citibase.

[3]However, a recursive structure may suffice if detailed knowledge of the economy is not required. For example, Moreno (1992b) uses a Choleski factorization to identify mutually orthogonal domestic and external shocks, and to measure the vulnerability of an economy to these external shocks under alternative exchange rate regimes.

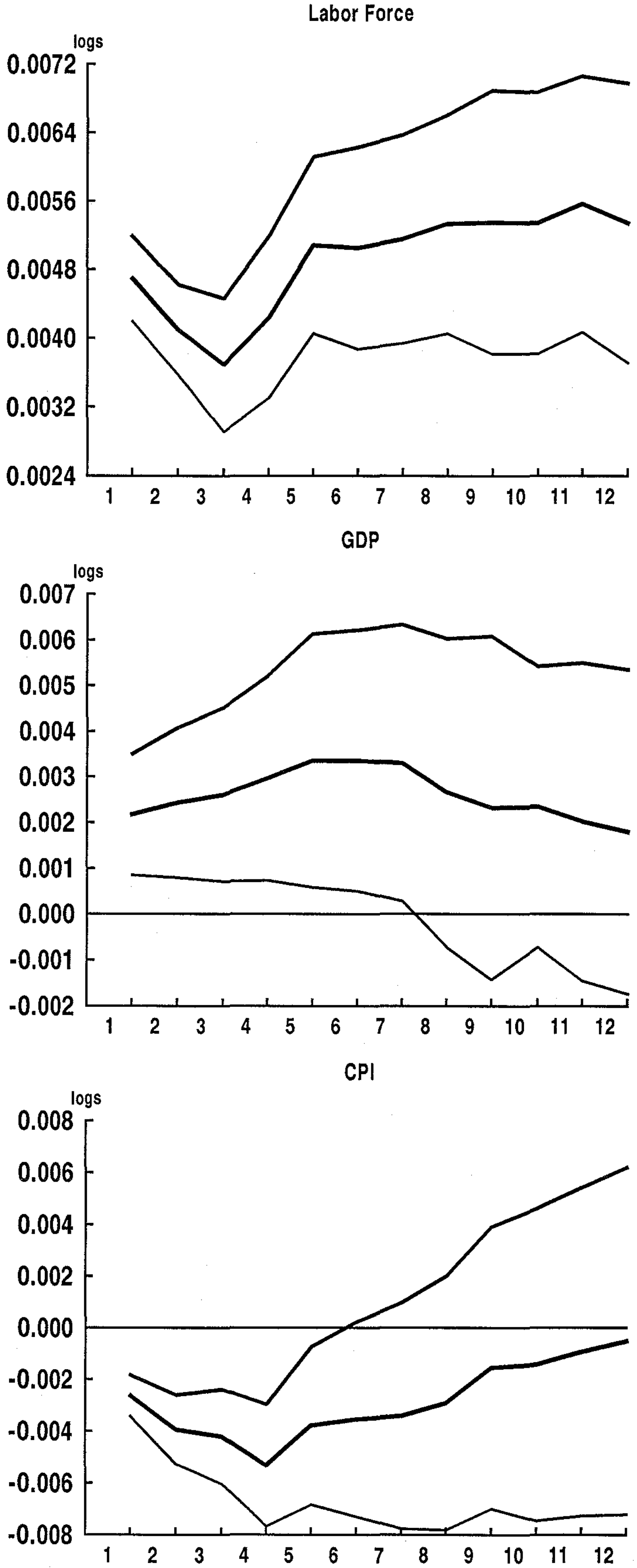
CHART C.1

RESPONSE TO OIL PRICE SHOCK



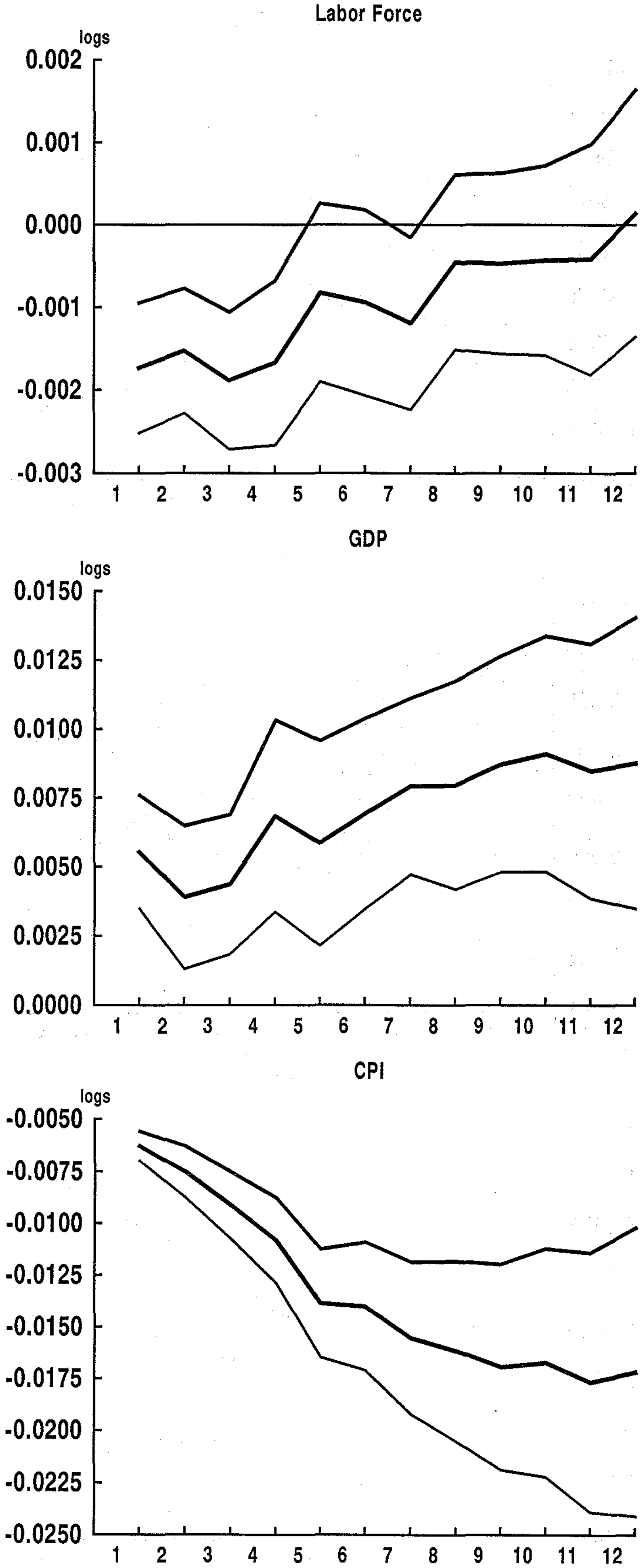
NOTE: Shock is one standard deviation.

CHART C.2
RESPONSE TO LABOR SUPPLY SHOCK



NOTE: Shock is one standard deviation.

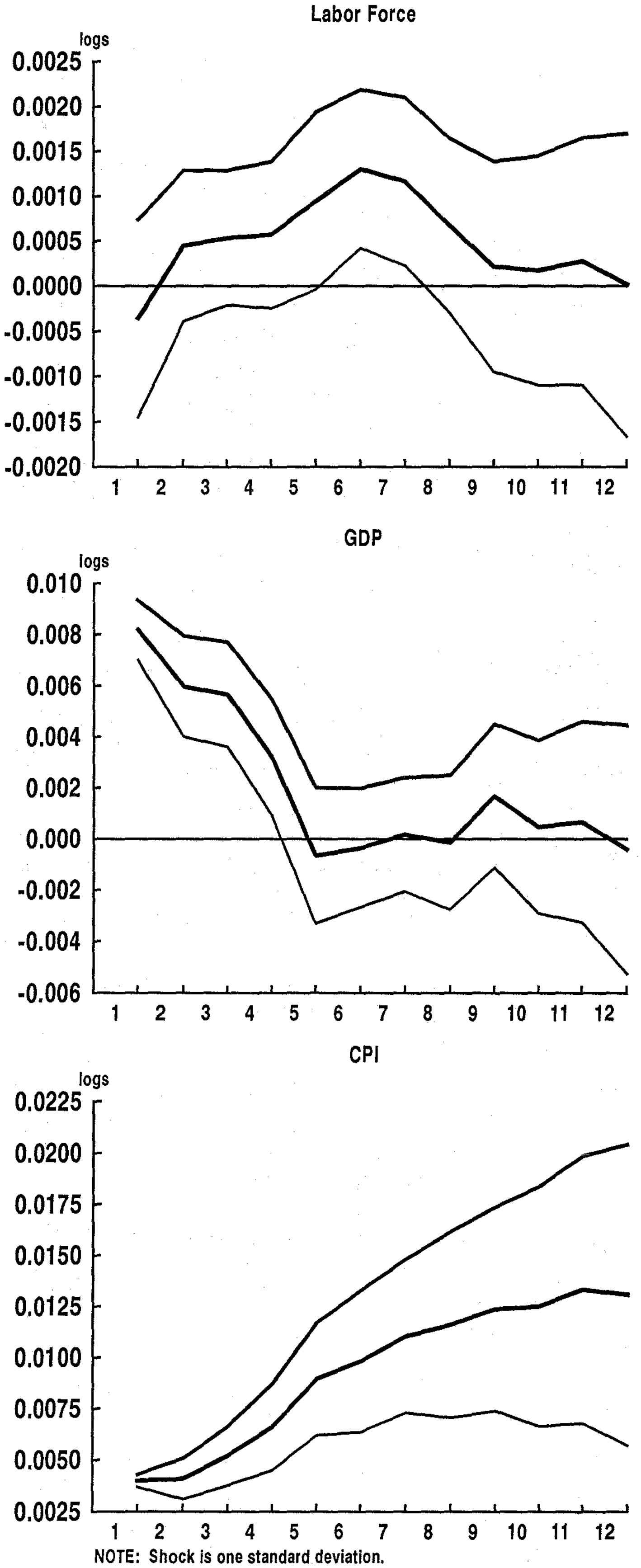
CHART C.3
RESPONSE TO TECHNOLOGY SHOCK



NOTE: Shock is one standard deviation.

CHART C.4

RESPONSE TO DEMAND SHOCK



NOTE: Shock is one standard deviation.

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Bank Holding Company Stock Risk and the Composition of Bank Asset Portfolios

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The author acknowledges the helpful comments of Jim Booth, Frederick Furlong, Sun Bae Kim, and Adrian Throop. Karen Trenholme provided excellent, and patient, research assistance.

In this paper, I conduct an empirical analysis of the behavior of bank holding company stock returns with the goal of identifying the effect of portfolio composition on the risks embodied in those returns. Using a modified arbitrage pricing theory model, I test for significant balance sheet effects on both the market and nonmarket components of bank stock systematic risk. I find that several categories of bank assets are significant in explaining bank stock risk profiles. Among other things, I discuss the importance of these findings in light of the risk-based capital standards and suggest that noncredit types of risk may need to be incorporated into bank capital standards if capital levels are to reflect risk accurately.

A common theme in recent discussions of U.S. banks and banking markets is the evaluation of risk. While it is widely accepted that banks are in the business of taking and managing risks, the question arises why some banks are riskier than others, even in the face of similar economic conditions. This theme has been echoed in the press, in academic studies, and in speeches given by government officials and bank regulators. The importance of understanding the determinants of bank risk has been heightened by the recent poor performance of U.S. banks as well as by the ongoing incidence of bank failures. Moreover, the issue becomes a public policy concern each time another banking organization fails, thus requiring the FDIC to step in and spend funds out of its already diminished reserves.

In recent months, much of the discussion relating to bank risk has involved the risk-based capital standards being phased in among the Group of 10 countries in Europe, North America, and Asia. These standards require banks holding riskier assets to maintain a larger capital cushion against losses, thereby reducing the likelihood that losses will deplete bank capital and lead to failure. Unlike traditional capital regulations that establish a fixed amount of capital (relative to assets) for all institutions, the risk-based standards set a variable capital cushion based on the perceived credit risk of the bank's underlying assets.

In setting the appropriate amount of capital an institution must hold, the risk-based capital standards assign bank assets to a small number of categories, each with its own apparent degree of riskiness and, thus, its own risk weight. The categories (and the weights) were determined based on assessments of the credit risk associated with different classes of bank assets. Some critics of the risk-based capital requirements argue that the categories are too crude to be meaningful, that is, they ignore important information relevant to determining the risk of bank assets in order to streamline the standards and make them easier to implement. Others criticize the standards for failing to address non-credit types of risk, such as interest rate risk and asset concentration risk.

In the current study, I attempt to identify some of the determinants of bank risk by evaluating the influence of bank portfolio composition on the behavior of bank holding company stock returns. In an earlier study (Neuberger 1991), I estimated the sensitivity of bank stocks to overall stock market conditions and to changes in interest rates. I showed that these sensitivities have varied considerably over time and that significant differences exist among banks in the sensitivities their stocks display to these two factors. Starting from a similar perspective in the current work, I relate the observed sensitivity of bank stock returns to the composition of bank asset portfolios. If bank risk is explained at least partially by the decisions banks make in allocating funds among different assets, then we should observe systematic variations in bank stock sensitivity based on the profile of their asset portfolios.

A related goal of the current work is to evaluate bank stock risk in light of the risk-based capital standards. More specifically, I attempt to determine if some of the classes of assets considered less risky under the risk-based standards actually do exert less of an impact on the risk of bank stocks. For example, are single-family mortgage loans a "safer" investment than loans to private businesses? The risk-based capital standards assert that they are by requiring banks to hold half as much capital in support of a residential mortgage than a commercial and industrial loan. The analysis below sheds some light on whether such distinctions are empirically important by estimating the effect these different classes of assets have on bank stock risk.

I. Bank Stock Risk and Bank Portfolios

In order to address the role of portfolio composition on bank stock risk, I need an appropriate model of bank stock returns. One basic model of asset returns is the Capital Asset Pricing Model (CAPM), developed by Sharpe (1964) and Lintner (1965). In this model, the return on a company's equity shares over and above the return on a riskless asset is explained solely as a function of the return on the "market portfolio," a perfectly diversified portfolio of all assets. In practical applications of the CAPM, a broad-based stock market measure, such as the return index on the S&P 500, is used as a proxy for the return on the market portfolio, and the risk-free rate of return often is ignored. This model segregates asset risk into two broad categories: risk that is related to the return on the market portfolio, called market or systematic risk, and risk that is unrelated to the market return, so-called nonsystematic or residual risk.

The "market model" can be summarized by the equation:

$$(1) \qquad R_{jt} = \alpha_j + \beta_j R_{Mt} + \epsilon_{jt},$$

where R_{jt} is the return on asset j in period t, R_{Mt} is the return on the market portfolio of stocks, β_j is an estimated coefficient that represents the sensitivity of the return on asset j to overall stock market returns, α_j is an estimated constant term, and ϵ_{jt} is a residual.

The estimated beta value from equation (1) measures the covariance of the individual asset's return with the return on the overall stock market. If the asset return moves in proportion to changes in the overall market's return, then the estimated value of β_j will be close to 1. Such assets are said to have average market-related risk. An asset with β_j greater than 1 carries above average market risk and typically must provide an above average expected return in order to induce investors to hold it. The equity shares of banks holding well-diversified portfolios of assets are likely to exhibit about average market risk.

Despite the theoretical appeal of the CAPM, it often has been found wanting in empirical applications. More specifically, factors in addition to the return on the market portfolio have been found to be significant in explaining the returns on individual assets. For example, Stone (1974) suggested an extension of the basic CAPM formulation. He reasoned that asset returns ought to depend not only on the return on the market portfolio of stocks, but also on the return on an alternative debt instrument. This "two-index model" identifies two sources of systematic risk for asset returns: The first is equivalent to the systematic risk of the CAPM and is the risk associated with the return on the market portfolio; the second is related to returns on debt securities and is sometimes referred to as interest rate risk. Residual risk in this model is any risk that is unrelated either to the market return or to interest rates.[1]

It is notable that the stock returns of most companies do not exhibit any significant sensitivity to the debt return variable of the two-index model. However, the asset and liability characteristics of financial intermediaries would seem to make them likely candidates for significant sensitivity to interest rate changes. Bank and thrift holding company stock returns thus have been a frequent object of study by financial economists. The evidence on the interest rate sensitivity of financial intermediaries, however, is mixed. Chance and Lane (1980) and Sweeney and Warga (1986) found that financial institutions tended not to have consistent or significant sensitivity to changes in interest rates. They showed, instead, that the stocks of utilities as a group exhibited more pronounced interest rate risk than

[1]Stone (1974) originally proposed the two-factor model by appealing to an intuitive argument that asset returns ought to depend on alternative investments in the stock and bond markets. However, the model has a sound theoretical basis since it can be derived from Merton's intertemporal CAPM (1973).

any other industry grouping. In contrast, a number of other studies have shown that the stock returns of financial intermediaries do exhibit significant, though not necessarily stable, interest rate risk. Among the studies finding significant interest rate sensitivity at banks and thrifts are those conducted by Martin and Keown (1977), Lloyd and Schick (1977), Lynge and Zumwalt (1980), Beebe (1983), Flannery and James (1984a, 1984b), Booth and Officer (1985), Kane and Unal (1988), and Neuberger (1991).

Some authors have attempted to explain the market and interest rate sensitivity of bank stock returns by looking at bank operations, portfolio composition, or other market conditions. Rosenberg and Perry (1981) conduct such a study using the CAPM framework, while Dietrich (1986) uses a two-index approach to explain the risk sensitivity of bank stocks as a function of bank balance sheet composition. Both of these studies find some evidence that individual bank characteristics affect the risk of bank stock returns. Moreover, as these characteristics change over time, the risks of bank stocks also change.

Several studies of bank stock returns have focused specifically on their interest rate sensitivity. Some of this research arose over concerns that maturity mismatches by financial intermediaries may have left them dangerously exposed to interest rate swings. This may have been particularly important for thrift institutions in the early 1980s. Flannery and James (1984a), for example, derive a measure of maturity mismatch between bank assets and liabilities. After estimating a two-index model on a cross section of intermediary stock returns, they relate the estimated interest rate coefficients from this regression to their duration gap measure. They find that the maturity mismatch is significantly related to the observed interest rate risk of the bank and thrift stocks they study.

Both the CAPM and the two-index model can be considered special cases of a more general asset pricing framework, known as the arbitrage pricing theory (APT, Ross 1976). In this framework, asset returns are explained by their relationship to a number of common factors. The return on the market portfolio of stocks may be one such factor; changes in interest rates could be another. However, this more general framework allows for many other influences to affect asset returns in a systematic way. In its most general terms, the APT suggests that asset returns can be represented by the following process:

$$(2)\quad R_j = a_j + b_{j1}I_1 + b_{j2}I_2 + \ldots + b_{jn}I_n + e_j,$$

where the Is are the common factors or indexes that systematically affect asset returns and the bs (also called factor loadings in APT parlance) represent the sensitivity of the asset to the different indexes.

Equation (2) describes the process that generates asset returns. By itself, it says nothing about how financial assets should be priced in equilibrium. Nevertheless, the APT is an equilibrium asset pricing model. Like the CAPM, this model argues that only systematic risk matters for the pricing of assets. It ignores nonsystematic risk because such risk can be diversified away. In the APT, the systematic risk of any asset is characterized by the vector of bs from equation (2). This vector can be thought of as a multidimensional version of the market beta from the CAPM. According to the APT, assets that exhibit the same systematic risks must be priced in equilibrium to offer the same rate of return. If not, then investors could buy and sell the different assets and risklessly profit from the transaction. Opportunities for such riskless arbitrage prevent assets from selling at anything but their equilibrium prices.

The vector of bs from equation (2) summarizes the systematic risk of an asset and, according to the APT, is the primary determinant of the asset's price. This implies that the expected return on any asset can be described as a function of its vector of factor loadings. The theory also implies that each of these factor loadings should be "priced" in equilibrium. This means that every b should be associated with a risk premium. These risk premia measure the increased return that an investor receives for bearing the systematic risk associated with the corresponding factors and can be estimated using the equation:

$$(3)\quad E(R_j) = \lambda_0 + \lambda_1 b_{j1} + \lambda_2 b_{j2} + \ldots + \lambda_n b_{jn},$$

where λ_i is the risk premium that measures the increase in expected return for a one-unit increase in the ith factor loading.[2]

The APT predicts that all assets are affected by the same set of systematic factors. Unfortunately, the model provides no guidance as to which factors are important in explaining asset returns. A number of studies have attempted to identify possible sets of factors that are common across broad portfolios of assets (see, for example, Chen, Roll, and Ross 1986). In contrast to the factors, the APT predicts that asset risk profiles (that is, the set of factor loadings) differ across assets and likely depend on characteristics that are specific to each asset. Little empirical work has been done to investigate the characteristics of individual assets that are important in explaining their risk profiles.

[2]In applications of the APT, equation (2) is sometimes estimated for a sample of assets (or portfolios of assets) over a particular time period. The estimated vector of bs is extracted from these estimates, and then is used to estimate equation (3) over a different time period. This two-step procedure yields estimates of the risk premia associated with the different factors.

It is reasonable to assume that these risk profiles (the *b*s from equation (3)) depend on some distinguishing characteristics of each asset. In the case of banks, recent developments in capital regulation suggest that regulators view the composition of bank asset portfolios as an important determinant of bank risk. The risk-based capital guidelines set different required levels of capital for each of a number of categories of bank assets. These asset categories were established based on perceptions of the relative credit risks of the different assets. Box 1 provides some detail on the risk weights of several broad groupings of bank assets. In this paper, I use a modified APT model to test whether the stock market confirms this regulatory view that portfolio allocations are significant in explaining the risk of bank holding company stock returns.

Box 1

Selected Asset Categories and Risk Weights under the Risk-Based Capital Standards

Asset Category	Risk Weight
Treasury and Government Agency securities (includes GNMA mortgage-backed securities)	0 percent
FNMA and FHLMC mortgage-backed securities	20 percent
Privately issued mortgage-backed securities and residential mortgage loans	50 percent
Commercial & industrial loans and loans to individuals	100 percent

The risk-based capital standards set minimum capital ratios at 8 percent of risk-weighted assets. More specifically, the standards call for Tier 1 capital (mostly equity) of at least 4 percent, and sufficient Tier 2 capital to bring the total to 8 percent. Risk-weighted assets are determined as the book value of assets in each of the different categories multiplied by the corresponding risk weight. In effect, this means that banks must hold the full 8 percent of capital against assets in the 100 percent risk weight category, 4 percent against the 50 percent risk-weighted items, and no capital against zero risk-weight assets like Treasury securities.

The risk-based capital standards also establish required levels of capital to support off-balance sheet activities, such as interest rate and foreign exchange swaps and options. The required amounts of capital for these activities generally depend on the type and maturity of the contract and the cost of replacing an existing contract with a new one. These capital requirements are intended to reflect the credit risk associated with these activities and do not currently incorporate any hedging effects they may have on the interest rate or foreign exchange risk of the bank.

In this model, I assume there is one common factor for all bank stocks, namely, the return on the market portfolio. I then hypothesize that the proportion of bank portfolios allocated to different assets represents a set of characteristics that are important determinants of their risk profile and thus are significant in explaining bank stock returns. Defining P_{ji} as the proportion of the *i*th asset (relative to total assets) in the portfolio of bank *j*, this model can be expressed as

$$(4) \qquad R_{jt} = \alpha_j + \beta_j R_{Mt} + \textstyle\sum_i \lambda_{ji} P_{jit} + \epsilon_{jt}.$$

While equation (4) captures the direct effects of portfolio composition on bank stock returns, these asset shares also may exert an indirect influence by altering the market risk of bank stock returns. The original market model views an individual asset's beta as constant over time. However, subsequent research confirms that the sensitivity of bank stocks to the market portfolio (as well as to other systematic factors) is not constant (Kane and Unal 1988, Kwan 1991, Neuberger 1991). One interpretation of the market beta is that it represents an average of the market risks associated with each of the assets in the bank's portfolio. Changes in the bank's asset mix, therefore, will change the overall market risk of the bank's stock returns. I test for these indirect effects by allowing the estimated coefficient β_j to depend (at least partially) on the proportion of the bank's assets allocated to different asset categories.[3] This dependence changes somewhat the interpretation of the direct effects: The estimated λ coefficients from equation (4) reflect the influence of portfolio composition on the nonmarket component of systematic risk.

I assume that the relationship between asset allocations and estimated beta values is additive. Thus, the hypothesis that market risk is variable and depends on portfolio composition can be expressed as

$$(5) \qquad \beta_{jt} = \gamma_{j0} + \textstyle\sum_i \gamma_{ji} P_{jit} + \eta_{jt},$$

where each coefficient γ_{ji} represents the impact of asset share *i* on the stock market sensitivity of bank *j*'s equity, and γ_{j0} is the portion of market risk that is unrelated to the bank's asset allocations. If portfolio composition affects the market risk of bank stocks, then the estimated values of γ_{ji} should differ significantly from zero. The sign of these coefficients will determine whether the specific asset categories increase or decrease the sensitivity of the bank's stock return to the overall stock market.

These relationships can be expressed in a single equation by substituting equation (5) into equation (4):

[3]This dependence also means that the estimated coefficient varies over time and thus requires a time subscript in the subsequent equation.

$$(6) \qquad R_{jt} = \alpha_j + \gamma_{j0} R_{Mt} + \textstyle\sum_i (\gamma_{ji} P_{jit}) \bullet R_{Mt} + \sum_i (\lambda_{ji} P_{jit}) + v_{jt},$$

where v_{jt} is a combination of the error terms from equations (4) and (5). The dependence of the stock market beta on the composition of the bank's balance sheet adds several "interacted" variables to the empirical model. The interactions are between the return on the market portfolio of stocks and the asset share variables from the bank's portfolio. The coefficients on these interaction terms measure the indirect effects of portfolio composition on the estimated market risk of bank stocks.

An additional bank characteristic that may influence bank stock returns is the financial leverage of the bank. Since banks are subject to capital regulation, there are regulatory limits on the extent to which banking firms can leverage their operations. Nevertheless, many banks choose to hold more (sometimes significantly more) than the required minimum level of capital. Option-based models of bank risk take explicit account of leverage. In the market model approach, leverage effects are implicitly assumed to affect the market beta. In order to isolate these leverage-related differences in risk, I interact bank leverage with the return on the market portfolio. The empirical model becomes

$$(7) \qquad R_{jt} = \alpha_j + \gamma_{j0} R_{Mt} + \delta_j LEV_{jt} \bullet R_{Mt} + \textstyle\sum_i (\gamma_{ji} P_{jit}) \bullet R_{Mt} + \sum_i (\lambda_{ji} P_{jit}) + v_{jt},$$

where LEV_{jt} is the book value of assets divided by the market value of bank equity, and δ_j is an estimated coefficient that reflects the influence of bank leverage on the market risk of bank stock returns.

I make one final adjustment to the model based on econometric considerations. Equation (7) estimated on a time series, cross-section of banking firms constrains the estimated constant term (α in the equation) to be identical across all banks in the sample and over the estimation interval. This constraint may not be appropriate and may bias the estimation results. To account for time-specific effects that may affect all banks in the same way, I add time dummy variables (omitting the first period) to all of the regressions.[4] I do not account for differences in the constant term across banks because I expect that most of the cross-sectional variation in the sample will be captured by the balance sheet variables. Since there is no economic significance to the coefficients on these time period dummy variables, I do not report them in the next section.

In evaluating the results presented below, it is important to recognize that bank stock returns may not be the ideal vehicle for identifying the determinants of risk that may be of interest to bank depositors or regulators. Ideally, it would be preferable to obtain a direct measure of bank asset or portfolio risk, and then search for the determinants of that measure of risk. Unfortunately, such direct measures typically are not available. One way around this problem is to use an option pricing framework to evaluate bank risk. This modeling approach provides an indirect measure of bank asset risk based on the behavior of bank stock and option prices. Examples of option-based models of bank risk include studies by Levonian (1991), and Cordell and King (1992).

In contrast to either direct or indirect measures of bank asset risk, the risk of bank holding company stock returns reflects the market's perception of an amalgam of risks associated with operating a bank. These include asset risk, default risk, deposit insurance risk, charter value risk, etc. Focusing on the risks of holding bank stocks does not provide specific evidence regarding bank asset risk. For example, an increase in bank asset risk will have a positive effect on bank stock risk, but the risk of holding bank stocks could rise for reasons other than an increase in asset risk. Nevertheless, the work presented here does provide important insights into how bank portfolio allocation decisions influence the market's perception of the combination of risks incorporated in bank stocks.

II. *Empirical Results on Bank Portfolio Composition and Bank Stock Risk*

In this section, I present the results from estimating equation (7) on a sample of 119 bank holding company stock returns over the quarterly interval from 1988 to 1990. The data for (monthly) bank stock returns are drawn from the Compustat bank tapes, are adjusted for dividends and splits, and then are summed to a quarterly frequency. The balance sheet data are taken from quarterly Reports of Condition (Call Reports).

Having two different sources of data for stock returns and balance sheets poses an interesting problem for the empirical work. The stock return data are for bank holding companies. The balance sheet data are for individual banks. The problem is that many of the larger bank holding companies from the Compustat database own or control multiple banks. In combining balance sheet data with the holding company stock returns, it is desirable to have

[4] An alternative method for incorporating the influence of time-specific factors on stock returns is to include a time trend variable in the regressions. This procedure, however, imposes a particular structure on the impact of time on the banks in the sample, namely, it requires this effect to be linear. The procedure used here avoids that restriction while still capturing the impact of time-specific events that influence all banks in a similar way.

accounting data that accurately represent the balance sheet of the holding company. One solution used in previous work (e.g., Flannery and James 1984a and Kwan 1991) is to use accounting data from the largest bank subsidiary of the holding company and to limit the sample to those lead banks that hold at least, say, 75 percent of total holding company assets. For the current project, I summed individual bank data from the Call Reports, thereby building up more complete balance sheets for holding companies with multiple bank subsidiaries. The combined balance sheet data used in this study average well over 90 percent of holding company assets during the four-year estimation interval, considerably higher than in previous studies. The database also includes significant changes in bank structure during this period, as it was necessary to keep track of subsidiary sales and purchases, bank mergers and acquisitions, as well as failures and other resolution procedures. The result of this extensive data project is a consistent sample of 119 of the largest bank holding companies in the U.S. over the 12-quarter interval from 1988.Q1 to 1990.Q4.[5]

All of the reported results are from pooled regressions; no individual bank estimates are reported. Thus, the coefficients represent average estimated coefficients for the banks in the sample. The asterisks in the table reflect the degree of statistical significance of the estimated coefficients. The coefficient for R_M is tested against a null hypothesis that the group of stocks exhibits average market risk, that is, that the value of beta is one. All other tests are performed against a null hypothesis that the estimated coefficient is equal to zero.

Finally, in pooled cross-section regressions of the type presented here, heteroskedasticity is a common problem that can bias estimated standard errors and thus measures of statistical significance. A frequently used procedure to obtain consistent estimates of the covariance matrix and coefficient standard errors is that proposed by White (1980). In all of the regressions reported in this paper, I have employed White's technique to obtain consistent estimates of standard errors.[6]

In Table 1, I present the regression results from the model of bank holding company stock returns using several non-overlapping categories of securities and loans. These asset groups comprise on average about 60 percent of the assets of the banks in the sample. In addition to the on-balance sheet assets, I also include in column (8) of the table the sum of two of the largest categories of off-balance sheet activities: foreign currency and interest rate swaps, options, and other contracts.

In each succeeding column of Table 1, I include in the regression one more asset share variable. In this way, I can determine if an additional asset alters the previous estimates, thereby indicating the presence of multicollinearity among the different asset categories. As the results in the table indicate, the estimated coefficients are fairly stable across the different regressions. Most of the coefficients that are significant in one regression remain so in succeeding columns. Some point estimates do vary across the regressions, and there is a tendency for standard errors to rise somewhat, reducing the significance levels for some coefficients as more balance sheet variables are added.

The estimated value of the market beta ranges between 2.7 and 3.4, suggesting that the banks in the sample exhibited significantly higher than average market risk during this period.[7] Clearly this was an extremely volatile period for bank stock returns relative to the market portfolio of stocks. The leverage variable interacted with the return on the market portfolio is not statistically significant in any of the regressions. This means that differences in bank leverage appear to have no identifiable impact on the market risk of bank holding company stock returns, at least during the period of analysis used in this study.

Among the different categories of assets, the interacted term for the sum of Treasury and government agency securities has a negative coefficient that is statistically significant in all of the regressions. This category encompasses assets with the most favorable risk weights under the risk-based capital guidelines. This includes Treasury securities that require no capital support and mortgage-backed securities issued by FNMA and FHLMC that receive a risk weight of 20 percent. These results provide evidence that holdings of government securities exert a negative impact on the market risk of bank stocks. Banks with a greater proportion of Treasury and agency securities in their portfolios exhibit less stock return volatility with respect to overall movements in the stock market than banks holding a smaller proportion of these assets. This

[5]Although I originally collected data for the four quarters of 1987, preliminary regressions indicated that the 1987 data contained a number of anomalies. I therefore restrict the estimation interval to the 1988 to 1990 period.

[6]White's methodology may not be necessary if there is no evidence of heteroskedasticity in the sample. Tests for the existence of heteroskedasticity showed that it did exist in the current data set and that White's procedure was therefore appropriate.

[7]As in most empirical estimates of market-based models, the value of the market beta depends crucially on the selected time period. Estimated beta values have shown considerable volatility in previous studies (for example, Neuberger 1991). Estimates of the current model that included 1987 showed significantly lower estimated betas. Notably, the other estimated coefficients were relatively stable and quite close to those reported here.

Table 1

Regression Results: Bank Holding Company Stock Returns as a Function of Portfolio Composition, 1988-1990.

Independent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R_M	2.730***	2.758***	2.974***	3.101***	3.126***	3.400***	3.455***	3.445***
R_M • Leverage	−0.001	−0.003	−0.003	−0.003	−0.003	−0.003	−0.003	−0.003
(Treasury + Govt. Agency Securities)/Assets	0.081*	0.085*	0.081*	0.084*	0.087*	0.049	0.049	0.014
R_M • (Treas. + Govt. Agency Secs./Assets)	−3.656***	−3.045***	−3.037***	−3.172***	−3.273***	−3.006***	−3.022***	−2.431***
Private Mortgage Securities/Assets		−2.660**	−2.749**	−2.983**	−3.005**	−2.957**	−2.960**	−2.870**
R_M • (Private Mortgage Securities/Assets)		13.511	13.619	19.459	20.442	19.977	20.236	18.703
Commercial Real Estate Loans/Assets			−0.264***	−0.268***	−0.261***	−0.266***	−0.264***	−0.301***
R_M • (Coml. Real Estate Loans/Assets)			1.281	2.221*	2.827**	2.798**	2.742**	3.377**
1-4 Family Residential Loans/Assets				0.009	0.009	−0.006	−0.006	−0.028
R_M • (1-4 Family Residential Loans/Assets)				−1.920**	−1.938**	−1.822**	−1.779**	−1.424
Multifamily Residential Loans/Assets					−0.048	−0.169	−0.159	−0.201
R_M • (Multifamily Res. Loans/Assets)					−9.771	−8.810	−9.035	−8.269
Commercial & Industrial Loans/Assets						−0.098	−0.091	−0.102
R_M • (C & I Loans/Assets)						0.604	0.408	0.594
Loans to Individuals/Assets							0.014	−0.006
R_M • (Loans to Individuals/Assets)							−0.526	−0.202
Currency & Interest Rate Contracts/Assets								−0.004
R_M • (Curr. & Int. Rate Contracts/Assets)								0.070*
$\bar{R}^2$	0.460	0.470	0.472	0.473	0.473	0.473	0.472	0.472
Number of Observations	1428	1428	1428	1428	1428	1428	1428	1428

Note: Sample includes 119 banks. Test for R_M is against null hypothesis that coefficient is equal to 1.0; all other tests are against null hypothesis that coefficients equal zero. Regressions also include dummy variables for each time period (except 1988.Q1); coefficients on these variables are not reported.

Significance: * = 10 percent level
** = 5 percent level
*** = 1 percent level

result is sensible in light of the relative safety of government securities with respect to default risk. Of course, such securities may expose banks to interest rate risk. The regressions provide some modest support for the existence of significant nonmarket risk associated with these securities. The first five columns show a positive coefficient on the noninteracted government securities variable that is significant at the 10 percent level. The significance of this coefficient disappears in the subsequent regressions, suggesting that the stock market may not price the extramarket risk of these securities in bank portfolios.

For the other category of securities, privately issued mortgage-backed securities, the interacted coefficient is not statistically different from zero in any regression. These securities do not exert any statistically significant impact on the market risk of bank stock returns. However, this asset category does have a stable and significant negative noninteracted coefficient. Larger portfolio shares of private mortgage securities are associated with lower bank stock returns. The stock market in effect imposes a "negative risk premium" on banks with proportionately higher exposure to the nonmarket systematic risks of holding these securities. Apparently, the market considers this exposure to be relatively "safe" for banks, and thus they receive a lower stock return for assuming it.

Among the different loan categories in Table 1, commercial real estate loans exhibit the strongest effect on bank stock returns. The estimated coefficient on this interacted variable is significantly positive in all but the first regression, indicating that these loans increase bank market-related risk. Stock returns of banks with a greater proportion of their assets in commercial real estate loans exhibit greater sensitivity to changes in the overall stock market. At the same time, the noninteracted variable for these loans has a significant and negative coefficient. This suggests that the nonmarket risk of these loans may actually be negative.

The only other loan category to exhibit any significant effect on bank stock returns is the interacted term for one-to-four family residential loans. The estimated coefficient on this variable is negative in all of the regressions and is significant in all but the last column. These results provide support for the notion that home mortgages may reduce the market risk of bank stock returns.

Finally, I consider in column (8) the influence of off-balance sheet activities on bank stock risk and return. These activities have grown rapidly in recent years, especially at larger banks. Some critics suggest that the explosive growth of these activities has increased bank risk in significant, though difficult to measure, ways. Banks defend the use of these instruments by claiming that they provide a hedge against currency and interest rate risk. The risk-based capital standards require some capital support for off-balance sheet activities, recognizing that they entail some credit risk. However, the capital guidelines ignore any risk-reducing effects that such activities may have on currency or interest rate risk.

As the results in column (8) indicate, the off-balance sheet category has a positive and marginally significant estimated coefficient on the interacted variable, suggesting that these activities are associated with greater market risk for bank stock returns.[8] This finding provides some support for including off-balance sheet activities in the risk-based capital regulations and suggests that more work is needed to understand this rapidly growing market. Perhaps more important, the off-balance sheet activities do not show any statistically significant nonmarket risk effects. At least for the banks in the sample, it does not appear that off-balance sheet activities have reduced the extra-market risk of bank stock returns.

Interpretation of Results

The findings presented here highlight a number of interesting aspects regarding the risk of bank stock returns. First, portfolio composition appears to affect both the market and nonmarket systematic risks of bank stock returns.[9] Several categories of assets exert a statistically significant effect on bank market risk through the balance sheet variables interacted with the market return. In addition, several asset categories exert an impact on bank stock returns independent of market risk. In terms of the APT model, this latter finding suggests that the composition of a bank's asset portfolio may represent a set of characteristics that are significant determinants of its (nonmarket) systematic risk profile.

Second, the significant results among the interacted variables provide some interesting empirical evidence regarding the risk hierarchy of the risk-based capital guidelines. Holdings of government securities, for example, appear to

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[8]When the two types of off-balance sheet activities were included separately in the regressions, each showed the same statistically significant positive interacted coefficient and no significance for the noninteracted coefficient. However, putting both types of off-balance sheet activities in the same regression produced evidence of multicollinearity. Apparently, the same banks that use interest rate contracts are also those most heavily involved in foreign currency contracts. By combining the two categories into one, their combined effect can be estimated without any statistical problems arising from multicollinearity.

[9]As in all studies of this type, any hypothesis tests are tests of the joint hypothesis that (a) the modified APT model is correct, and (b) portfolio composition is an appropriate set of bank characteristics affecting bank stock returns.

reduce the market risk of bank stocks. This finding provides support for the preferential treatment given to Treasury and other government agency securities in the risk-based capital standards. The absence of credit risk inherent in these securities provides banks with a "safe haven" that is reflected in the reduced market risk of bank stock returns. The weak evidence on the nonmarket risks of government securities also may raise questions regarding the empirical importance of any interest rate risk associated with holding them.

Among several broad categories of bank loans, neither commercial and industrial loans nor loans to individuals have any significant effect on the market risk of bank stock returns. This finding is notable because these two categories of loans receive the highest risk weight under the risk-based capital standards and yet they do not appear to increase the market risk of bank stock returns. This result may raise some doubts as to whether the highest risk weight is appropriate for these categories of loans. In contrast, the results presented here support the preferential treatment given to residential mortgages under the risk-based capital rules. The regressions confirm that residential real estate loans exhibit a significant risk-reducing influence on the market risk of bank stock returns.

An additional interesting finding among the loan categories is the result for commercial real estate loans. These loans exert a strong positive effect on the market risk of bank stock returns. This finding highlights the real source of risk for banks making real estate loans. Even prior to the recent "real estate recession," the risky area of real estate lending for banks has been for commercial projects.

Turning to the noninteracted balance sheet variables, several significant direct coefficients suggest that the corresponding assets are important in explaining nonmarket systematic bank stock risk. Among these assets, government securities have a marginally significant positive risk premium associated with them, while private mortgage securities and commercial real estate loans are associated in the sample with significant negative risk premia.

However, the interpretation of these direct coefficients is somewhat uncertain. The regression model relates portfolio allocations to *realized* returns rather than expected returns as the theory suggests. A significant estimated noninteracted coefficient, therefore, could represent a fundamental relationship between bank stock returns and portfolio composition or it could be indicative of (good or bad) luck on the part of the bank in holding the particular asset during the estimation interval. This is particularly true given the relatively short time period over which the model is estimated. It is thus unclear, for example, whether commercial real estate loans systematically affect the nonmarket risk profile of bank stock returns or whether banks that made these loans in the 1988 to 1990 period were the victims of poor performance by these assets.

This same uncertainty should not affect the interacted coefficients in the regressions. These coefficients represent the influence on market risk of the particular asset category relative to the average market beta of the banks in the sample. Each asset in banks' portfolios may be considered to have its own associated market beta value. Thus, there may exist a "beta" for making residential mortgage loans or a similar measure for holding government securities. The aggregate beta that a bank exhibits thus will be a weighted average of the individual betas associated with the different assets in its portfolio. As the asset mix changes, so will the bank's market risk. If the market model is an appropriate representation of asset returns, then these interacted effects may be stable over time.

III. Conclusion

In the current paper, I conduct an empirical analysis of the behavior of bank holding company stock returns with the goal of identifying the effect of portfolio composition on the risks embodied in those returns. I find that several categories of assets in bank securities and loan portfolios do alter the risk profile of bank stock returns. Among other things, I discuss the importance of these findings in light of the risk-based capital standards and the different risk weight categories that those standards use. The risk-based capital guidelines are an important step in establishing regulations that measure bank risk more accurately. However, these standards may need to be modified as new evidence is uncovered about the risk effects of different bank activities. Moreover, as banks respond to a changing economic and regulatory environment, their asset mix may change and alter the risk profile of their portfolios. This undoubtedly has happened, for example, with respect to off-balance sheet activities. Capital regulation may need to respond as well to these changing realities if required capital levels are to reflect bank risk accurately.

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