Bank Loan Components and the Time-Varying Effects of Monetary Policy Shocks

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Abstract

The impulse response functions (IRF) of an aggregate variable is time varying if the IRFs of its components are different from each other and the relative magnitudes of the components are not constant—two conditions likely to be true in practice. We model the behavior of loan components and document that the induced time variation for total loans is substantial, which helps to explain why studies describing total loans have had such a hard time finding a robust response of total bank loans to a monetary tightening.

Keywords: Small and large banks, VAR, impulse response functions

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1 Introduction

Relationships between key macroeconomic variables are often changing over time. For example, several articles have pointed out that responses of variables like GDP and the unemployment rate to (structural) shocks are different when they are estimated using post-1980 data, than when they are estimated using pre-1980 data. During the coming years, much research is likely to be devoted to the question whether, given the recent financial crisis, a new era has started in which responses are again different.

The standard procedure to uncover the responses of economic variables to shocks is to estimate a structural vector autoregressive system (VAR) and to calculate the impulse response functions (IRFs). To deal with *time-varying* responses in VARs one could simply split the sample or use rather complex Bayesian methodologies that allow all parameters of the VAR to change over time.

It is important to understand why responses can change over time. Not only does this help us to comprehend the underlying economics better, it also sheds light on what econometric technique to use to deal with the time-varying aspects of the problem. In this paper, we emphasize that the percentage response of an *aggregate* variable will only be constant through time if the percentage responses of its components *and* the relative magnitudes of the components have stayed the same.[1] Even if the responses of the components are not time varying, then the response of the aggregate variable will depend on the relative magnitudes of the components when the shock occurs, and, thus, be time varying if the relative importance of the components is time varying. In other words, the response of the aggregate variable depends on the initial conditions of the components. If the relative size of the components is cyclical, then the response of the aggregate variable will itself be cyclical. If there is a low-frequency change in the relative size of the components, then there will be a gradual change in the response of the aggregate variable.

The consequence of using aggregate data for time-varying IRFs has received little attention in the literature, even though the use of aggregate data is widespread. To illustrate the quantitative importance of the time variation induced by aggregation, we

[1] As discussed in more detail in the next section, we focus on the commonly used log-linear specification.

model the behavior of the loan components and then show that the implied time-variation in the response of total loans is substantial. The three loan components are commercial and industrial (C&I) loans, consumer loans, and mortgages.

There are three reasons why loans are interesting to consider. First, Den Haan, Sumner, and Yamashiro (2007, 2009) document that the responses of these three loan components following a monetary tightening are quite different. In particular, whereas consumer loans and mortgages decrease following a monetary downturn, C&I loans *in*crease. All responses are economically and statistically significant. This is found to be the case for both Canadian and US bank loans and for different samples. In this paper, we extend the results of Den Haan, Sumner, and Yamashiro (2007, 2009) and show that this result is found for both small and large banks.[2] In contrast, during a non-monetary downturn the largest drop is found for C&I loans.[3]

Second, the relative magnitudes of these loan components have changed a lot. The share of real estate loans has increased for both small and large banks. For small banks the counterpart is mainly a reduction in consumer loans and for large banks it is a reduction in C&I lending.

The two findings that the bank loan components move in different directions and that their relative magnitude has changed over time suggest that it may not be that easy to find a robust response of total bank loans. In fact, Gertler and Gilchrist (1993) point out that while conventional wisdom holds that a monetary tightening should be followed by a reduction in bank lending, it has been surprisingly difficult to find convincing time-series evidence to support this basic prediction of economic theory. The third reason to focus on bank loans is that it may shed light on this puzzle. That is, the response of total loans is not robust and a researcher may interpret this as a sign that it is time varying. We show that the changes in the loan shares themselves predict a substantial variation in the response of total loans even if the responses of the loan components are not time varying.

[2] The robustness is remarkable given that Kashyap and Stein (1995) find more substantial differences between the behavior of small banks and large banks in several aspects.

[3] A non-monetary downturn is an economic downturn that is not associated with an increase in the interest rate.

In the econometrics literature, there are many papers that deal with aggregation.[4] These papers typically focus on the misspecification of the time-series model with aggregate variables and the efficiency of the estimation procedure. Moreover, linear frameworks are typically used.[5] The focus of our paper differs from this literature. First, although our time-series model is very simple, it is nonlinear because the logarithms, not the levels of the variables, enter the VAR. Recall, that the logarithm of the aggregate variable is not the sum of the logarithms of the components; it is a nonlinear function of the components. In addition, we are mainly interested in the implication of this commonly used nonlinear setup that the impulse response function of an aggregate variable is time varying.[6]

The rest of this paper is organized as follows. In Section 2, we explain why the impulse response function of a variable that is the sum of other variables in a log-linear system is time varying. Section 3 discusses the data used and the empirical methodology. Section 4 reports the results for the bank loan components, and Section 5 documents the time-varying responses of total loans implied by the estimated VAR with loan components. Section 6 documents that our reason for time variation, i.e., changing weights, can explain part of the time variation found in the estimates for total loans obtained using rolling windows. The last section concludes.

2 Time-varying impulse response functions

In this section, we show that the impulse response functions of aggregate variables in disaggregated log-linear systems are, in general, time varying.[7] In particular, the aggregate responses depend on the (relative) initial values of the micro components, which are, of course, stochastic and depend upon the history of shocks. We will see that even the

[4] See, for example, Granger (1980) and Pesaran, Pierse, and Kumar (1989).

[5] An exception is van Garderen, Lee, and Pesaran (2000).

[6] See Potter (1999) for an overview of non-linear time-series models.

[7] The econometrics literature on the advantages and disadvantages of disaggregated models typically considers linear systems. In a linear system, the implied impulse response functions of aggregate variables would *not* be time varying (unless at least one of the impulse response functions of the components is time varying). In practice, one typically uses log-linear systems to ensure that the effect of a shock, expressed as a percentage change, does not depend on the value of the variable.

shape and sign of the impulse response functions of aggregate variables can change over time. It is important to realize that the aggregate responses are time varying even though the coefficients of the VAR are constant and the impulse response functions of the micro components are, thus, by construction not time varying.

To provide intuition we discuss a simple example in which we trace the behavior of an aggregate variable in response to a structural shock. The disaggregated system is as follows.

$$\ln(z_{1,t}) = \rho_1 \ln(z_{1,t-1}) + \sigma_1 e_t \tag{1a}$$

$$\ln(z_{2,t}) = \rho_2 \ln(z_{2,t-1}) + \sigma_2 e_t \tag{1b}$$

$$z_t = z_{1,t} + z_{2,t} \tag{1c}$$

Here $z_{1,t}$ and $z_{2,t}$ are the two micro components that add up to the aggregate variable z_t and e_t is a white noise structural error term with unit variance.[8] We focus on the responses of z_t to changes in the structural shock e_t.

2.1 Dependence on initial values

To understand why the response of the aggregate variable is, in general, time varying consider the formula for the k-th period percentage change in z_t.[9]

$$\begin{aligned} \frac{z_{t+k}-z_t}{z_t} &= \left(\frac{z_{1,t}}{z_t}\right)\left(\frac{z_{1,t+k}-z_{1,t}}{z_{1,t}}\right) + \left(\frac{z_{2,t}}{z_t}\right)\left(\frac{z_{2,t+k}-z_{2,t}}{z_{2,t}}\right) \\ &= \left(\frac{z_{1,t}}{z_t}\right)\widehat{z}_{1,k} + \left(\frac{z_{2,t}}{z_t}\right)\widehat{z}_{2,k} \end{aligned} \tag{2}$$

Thus, the percentage change in z_t is a weighted average of the percentage change in $z_{1,t}$ and the percentage change in $z_{2,t}$. The percentage changes in $z_{1,t}$ and $z_{2,t}$, $\widehat{z}_{1,k}$ and $\widehat{z}_{2,k}$, are by construction not time varying, since the laws of motion are linear. In contrast, the

[8] We assume that $|\rho_1| < 1$ and $|\rho_2| < 1$.

[9] Here we use the actual percentage change of z_t and pretend that Equations (1a) and (1b) give actual percentage changes in $z_{1,t}$ and $z_{2,t}$ instead of log changes. The argument is the same for the specification with logs, but the formula is less transparent.

weights, $z_{1,t}/z_t$ and $z_{2,t}/z_t$, are time varying, which implies that the percentage change in z_t is also time varying. The only exception to this occurs when the laws of motion for $z_{1,t}$ and $z_{2,t}$ are identical.

To illustrate the time-varying nature of the impulse response functions of z_t, we will focus on the case where $\rho_2 = \sigma_2 = 0$. Equation (1b) then becomes

$$\ln(z_{2,t}) = 0. \tag{3}$$

Even in this very simple case, for which $z_t = z_{1,t} + 1$ and the value of $z_{1,t}$ relative to $z_{2,t}$ is simply the value of $z_{1,t}$, the impulse response function of z_t will vary with the value of $z_{1,t}$. To document this dependence we plot, in Figure 1, the response of $\ln(z_t)$ to a one standard deviation shock to e_t for five initial values of $\ln(z_{1,t})$. The initial values range from two times the unconditional standard deviation of $\ln(z_{1,t})$ below the unconditional mean to two times the unconditional standard deviation above the mean. For low values of $\ln(z_{1,t})$ the response of z_t to a shock is low because the effect on z_t is dominated by the zero effect on $z_{2,t}$. For high values of $\ln(z_{1,t})$ the response of z_t is large because the effect on z_t is dominated by the strong effect on $z_{1,t}$. Even the shape of the impulse response function varies with the initial value of $z_{1,t}$. In response to the shock, the value of $z_{1,t}$ increases relative to the value of $z_{2,t}$. When $z_{1,t}$ is large this does not matter much since the movements of z_t are dominated by the behavior of $z_{1,t}$. Consequently, for high values of $z_{1,t}$ we get an impulse response function for z_t that is similar to the impulse response function of $z_{1,t}$. When $z_{1,t}$ is small, however, $z_{1,t}$ increases relative to $z_{2,t}$, meaning that changes in $z_{1,t}$ will become more important for movements in z_t in the periods following the shock. The figure shows that this effect can be so strong that the percentage change in the aggregate variable is initially increasing even though the percentage change in $z_{1,t}$ is (by construction) monotonically decreasing.

2.2 Effects of the first and subsequent shocks

Since the response of the aggregate variable depends upon the relative size of the micro components, the effect of the first shock in e_t will have a different effect than subsequent shocks. For example, consider the case in which $z_{1,t}$ is more responsive to e_t than $z_{2,t}$. A subsequent positive shock of equal magnitude, then always has a larger effect. The reason for this is that a positive shock will increase the relative magnitude of the more sensitive component, $z_{1,t}$, and this increase in $z_{1,t}$ causes the effect of a percentage change in $z_{1,t}$ on z_t to increase. We demonstrate this effect by doing the following. First we calculate the impulse response function of z_t using some initial conditions for $z_{1,t}$. Next we calculate the impulse response function of z_t using, as initial conditions, the values of $z_{1,t}$ observed in the period after the first shock. This second impulse response function, thus, does not measure the total effect of the two shocks but only the additional effect of the second shock. Again we focus on the case with $\rho_2 = \sigma_2 = 0$.

In this exercise we use two different values for $z_{1,t}$ at the time of the first shock. In particular, we consider values of $\ln(z_{1,t})$ that are equal to two standard deviations below and above the mean. These are the two extremes of the five initial values considered in Figure 1. The results are presented in Figure 2. The figure shows that when $z_{1,t}$ is already high relative to $z_{2,t}$, a further increase in $z_{1,t}$ in response to the first shock does not increase the sensitivity of z_t to the shock. Consequently, the effect of the second shock is only slightly bigger than the effect of the first shock. In contrast, when $z_{1,t}$ is low relative to $z_{2,t}$ the increase in $z_{1,t}$ strongly increases the sensitivity of z_t to the shock and the second shock will have a much bigger impact on z_t.

2.3 Relation to Wold decomposition

The aggregate variable z_t has a time-varying impulse response function, because it is not a linear function of the two components and, therefore, is also not a linear function of the structural shock e_t. Since it is a well-behaved stationary process, it has a Wold decomposition, which is a linear representation with an impulse response function that is *not* time varying. The (reduced-form) innovation of the Wold decomposition, however, is not equal to the structural shock, and the impulse response function implied by the Wold decomposition is, in general, not equal to the impulse response functions for the structural shock. This is true even in an example like the one used here in which the structural shock is the only innovation in the system. That the impulse response functions are not equal is quite obvious since the impulse response function of the structural shock is time varying, while the impulse response function of the Wold decomposition is not. There is, however, a link between the two impulse response functions. The time-varying impulse response function for the structural shock represents the MA structure conditional on $z_{1,t}/z_{2,t}$ being equal to a certain value. The Wold decomposition gives the unconditional MA structure and, therefore, is the average value of the conditional time-varying impulse response functions.

2.4 Aggregate versus disaggregate systems

If one is interested only in the "average" effect of a shock one may simply want to estimate a time-series model for the aggregate variable and focus on the implied Wold decomposition. In this case, there are several things to be aware of. First, in practical applications there are several structural shocks, and the Wold decomposition would not only be an average across initial conditions, but also across different structural shocks.

Second, simple disaggregated models can generate dynamics for aggregate variables that are quite complex. For example, Granger (1980) shows that aggregation of finite-order AR processes can generate long memory. It is, thus, possible that many lagged terms are needed to accurately capture the dynamics of the aggregate process, but in practice one may not have enough data to accurately estimate many coefficients. That is, if one estimates a univariate law of motion for the aggregate variable one could face a trade-off between the potential misspecification of a low-order specification and the inefficient estimation of a high-order specification.[10]

This second aspect is, of course, related to the question of whether there are advantages to using disaggregated time-series models even if one is only interested in the behavior of the aggregate time series. This question has already received a lot of attention in the literature, but is typically addressed using systems that are linear in the variables as opposed to the log-linear specification that is common in much applied work and used in

[10] On the other hand, there are circumstances when it is advantageous to estimate a time-series process for the aggregate variable. For example, this is appropriate if there is a negative covariance between the innovations to the micro components.

this paper.[11] Although it would be interesting to address the forecasting question in our log-linear framework, we do not do so in this paper.

3 Empirical methodology

In Section 3.1, we discuss the data set employed in our study. Section 3.2 contains a discussion of our empirical methods.

3.1 Data

The loan data we use are from the Consolidated Reports of Condition and Income (Call Reports). In addition, we use the federal funds rate, the consumer price index, and personal income from the Bureau of Economic Analysis (BEA).[12] The sample starts in the first quarter of 1977 and ends in the last quarter of 2000. More details on the data sources and definitions of the series are given in the appendix.

Small (large) banks are defined as those whose asset value is less (more) than the 90 percentile. As is well known, the largest banks have a disproportionately large share of assets. This is also true for the three loan components. Moreover, the relative importance of the top 10 percentile of banks has grown over time, as is documented in Table 1.

Figure 3 plots the year-to-year growth rate for both small and large banks for the three loan components. The figure shows that there are substantial differences between large and small banks. To document this in more detail, Table 2 displays standard time-series statistics for the growth rate of the three loan components. Additionally, the figure makes clear that there have been large swings in the series. The credit crunch of the early nineties is visible in all series except the real estate loan series for small banks.[13] For C&I loans this credit crunch was an extraordinary episode, but for the other loan series other large swings are observed over the sample period.

[11] See for example Pesaran, Pierse, and Kumar (1989) and Pesaran (2003).

[12] We use the income measure from the BEA, because it is also available at the state level and we consider regional models in related work.

[13] See Bernanke and Lown (1991).

Figure 4 plots, for large and small banks, the relative importance of the three loan components in banks' loan portfolio. The graph shows that since the early eighties both small and large banks have increased the share of real estate lending in their portfolio. Small and large banks have offset the increased share of real estate lending in different ways. Large banks have decreased the share of C&I loans, while small banks have decreased the share of consumer loans in their portfolio.

3.2 Identification

In Sections 3.2.1 and 3.2.2, we show how we estimate the behavior of the variables during a monetary downturn and a non-monetary downturn of the same magnitude, respectively.

3.2.1 Monetary downturn

The standard procedure to study the impact of monetary policy on economic variables is to estimate a structural VAR using a limited set of variables. Consider the following VAR:[14,15]

$$Z_t = B_1 Z_{t-1} + \cdots + B_q Z_{t-q} + u_t, \tag{4}$$

where $Z_t' = [X_{1t}', r_t, X_{2t}']$, X_{1t} is a $(k_1 \times 1)$ vector with elements whose contemporaneous values are in the information set of the central bank, r_t is the federal funds rate, X_{2t} is a $(k_2 \times 1)$ vector with elements whose contemporaneous values are not in the information set of the central bank, and u_t is a $(k \times 1)$ vector of residual terms with $k = k_1 + 1 + k_2$. We assume that all lagged values are in the information set of the central bank. In order to proceed one has to assume that there is a relationship between the reduced-form error terms, u_t, and the fundamental or structural shocks to the economy, ε_t. We assume that

[14] To simplify the discussion we do not display constants, trend terms, or seasonal dummies that are also included.

[15] If there are cointegration restrictions, then the estimates of a VECM would be more efficient. We follow the literature and estimate a VAR. Using a VAR when a VECM is appropriate means that there is some efficiency loss but because of the rate T convergence, this efficiency loss is small. On the other hand, erroneously imposing cointegration would lead to a misspecified system.

this relationship is given by:

$$u_t = \overline{A}\varepsilon_t, \tag{5}$$

where $\overline{A}$ is a $(k \times k)$ matrix of coefficients and ε_t is a $(k \times 1)$ vector of fundamental uncorrelated shocks, each with a unit standard deviation. Thus,

$$E\left[u_t u_t'\right] = \overline{A}\,\overline{A}'. \tag{6}$$

When we replace $\mathrm{E}[u_t u_t']$ by its sample analogue, we obtain $k(k+1)/2$ conditions on the coefficients in $\overline{A}$. Since $\overline{A}$ has k^2 elements, $k(k-1)/2$ additional restrictions are needed to estimate all elements of $\overline{A}$. A standard practice is to obtain the additional $k(k-1)/2$ restrictions by assuming that $\overline{A}$ is a lower-triangular matrix. Christiano, Eichenbaum, and Evans (1999), however, show that to determine the effects of a monetary policy shock one can work with the less-restrictive assumption that $\overline{A}$ has the following *block*-triangular structure:

$$\overline{A} = \begin{bmatrix} \overline{A}_{11} & 0_{k_1 \times 1} & 0_{k_1 \times k_2} \\ \overline{A}_{21} & \overline{A}_{22} & 0_{1 \times k_2} \\ \overline{A}_{31} & \overline{A}_{32} & \overline{A}_{33} \end{bmatrix} \tag{7}$$

where $\overline{A}_{11}$ is a $(k_1 \times k_1)$ matrix, $\overline{A}_{21}$ is a $(1 \times k_1)$ matrix, $\overline{A}_{31}$ is a $(k_2 \times k_1)$ matrix, $\overline{A}_{22}$ is a (1×1) matrix, $\overline{A}_{32}$ is a $(k_2 \times 1)$ matrix, $\overline{A}_{33}$ is a $(k_2 \times k_2)$ matrix, and $0_{i \times j}$ is a $(i \times j)$ matrix with zero elements. Note that this structure is consistent with the assumption made above about the information set of the central bank.

We follow Bernanke and Blinder (1992) and many others by assuming that the federal funds rate is the relevant policy instrument and that innovations in the federal funds rate represent innovations in monetary policy. Moreover, throughout this paper we assume that X_{1t} is empty and that all other elements are, therefore, in X_{2t}. Intuitively, X_{1t} being empty means that the Board of Governors of the Federal Reserve (FED) does not respond to contemporaneous innovations in any of the variables of the system. While we do believe that the FED can respond quite quickly to new information one has to keep in mind that the data used here are revised data, which means that the value of a period t

observation in our data set was not available to the FED in period t. Rudebusch (1998) points out that if the econometrician assumes that the FED responds to innovations in the contemporaneous values of the available original data, but estimates the VAR with revised data, the estimated coefficients will be subject to bias and inconsistency.

3.2.2 Non-monetary downturn

Den Haan, Sumner, and Yamashiro (2007) compare the behavior of the variables during a monetary downturn, that is, the responses to a negative monetary policy shock with the behavior of the variables during a non-monetary downturn, that is, the responses during a downturn of equal magnitude caused by real activity shocks. To be more precise, a non-monetary downturn is caused by a sequence of output shocks such that output follows the exact same path as it does during a monetary downturn.

The motivation for looking at these impulse response functions is the following. The impulse response functions for the monetary downturn not only reflects the direct responses of the variables to an increase in the interest rate, but also the indirect responses to changes in the other variables and, in particular, to the decline in real activity. This makes it difficult to understand what is happening, especially since a decline in real activity could either increase or decrease the demand for bank loans.[16] For example, if one observes an increase in a loan component during a monetary downturn it could still be the case that there is a credit crunch if a decline in real activity strongly increases the demand for that particular loan component. That is, without the credit crunch this loan component would have increased even more. By comparing the behavior of loan components during a monetary downturn with a non-monetary downturn, of equal magnitude, one can get an idea regarding the importance of the different effects.

Den Haan, Sumner, and Yamashiro (2007) argue that the comparison of the behavior of loans to monetary policy shocks and output shocks is useful in understanding what happens during the monetary transmission mechanism. In this paper, the comparison is

[16] The reduction in real activity would reduce investment and, thus, the need for loans, but the reduction in sales would increase inventories, which could increase the demand for loans.

used to address two questions. First, we want to understand whether the differences in the behavior of the loan components across the two downturns, documented by Den Haan, Sumner, and Yamashiro (2007) for all banks, is similar when one differentiates banks by size. Second, the impulse response function for the non-monetary downturn is simply an impulse response function, and when calculated for total loans will in principle be time varying. So this will provide another application to study the quantitative importance of time-varying impulse response functions for aggregate variables.

Implementing this exercise requires us to make an additional assumption on $\overline{A}$. In particular, we assume that shocks to real activity have no contemporaneous effect on any of the other variables.[17] Under this assumption, there is a simple way to calculate the impulse response functions. In each period one simply sets the value of aggregate real activity equal to the value observed during the monetary downturn, and one can then obtain values for the remaining variables by iterating on the VAR.[18] We can interpret the difference between the impulse response functions during a monetary downturn and during a non-monetary downturn as the effect of the increase in the interest rate holding real activity constant.[19]

The construction of a non-monetary downturn makes it convenient to quantitatively compare the responses, but one would obtain similar results by simply comparing the responses to a monetary policy shock with the responses to a *single* output shock.

[17] That is, the matrix $\overline{A}_{33}$ also has a block-triangular structure. Note that the block-triangular structure imposed in Equation 7 already made the assumption that the innovation to output had no effect on the federal funds rate.

[18] The assumption that shocks to real activity do not affect the other variables contemporaneously implies that we do not have to explicitly calculate the values of the structural shocks during a non-monetary downturn. It is possible to make other assumptions on $\overline{A}$ and still calculate the impulse response functions, but it would be slightly more cumbersome.

[19] In fact, the difference between these two impulse response functions is equal to the response to a shock in the federal funds rate when the response of the output variable is set equal to zero in every period.

4 Responses of loan components

The results discussed in this section are based on a VAR that includes the three loan components in addition to the federal funds rate, a price index, and a real activity measure. Our benchmark specification for the VAR includes one year of lagged variables, a constant, and a linear trend. We also include quarterly dummies since the data from the Call reports are not adjusted for seasonality.[20]

Output, the price level, and the interest rate response. Figure 5 plots the responses for output, the price level, and the federal funds rate. The results are consistent with those in the literature. The federal funds rate gradually moves back to its pre-shock value, with half of this adjustment occurring in the first year or so. Output declines, but with a delay and only reaches its maximum decline after two years. When we feed the VAR a series of output shocks that result in the same output decline, i.e., a non-monetary downturn, then the interest rate declines, which is consistent with the monetary authority following a Taylor rule. Finally, our results are subject to the price puzzle, with the price level increasing after a monetary tightening.[21]

[20] In addition, we estimated VARs for which the specification was chosen using the Bayes Information Criterion (BIC). We search for the best model among a set of models that allows, as regressors, the variables mentioned above and a quadratic deterministic trend. BIC chooses a specification that is more concise then our benchmark specification. The results are similar to those that are based on our benchmark specification.

[21] Several papers have suggested alternative specifications of the VAR to avoid the price puzzle. Examples are Christiano, Eichenbaum, and Evans (1999), Giordani (2004), and Romer and Romer (2004). Barth and Ramey (2001) argue instead that there could be a cost channel that pushes prices up during a monetary tightening and provide empirical evidence based on industry-level data to support their view. In our experience, a positive price response is a very robust empirical finding and we find little value in searching for that VAR specification that will give the desired price response. For example, Christiano, Eichenbaum, and Evans (1999) find that adding an index for sensitive commodity prices solves the price puzzle in their sample, but we find that this does not resolve the puzzle for our more recent samples. We also tried the measure of monetary policy shocks proposed by Romer and Romer (2004) and reestimated the VAR over the period for which this measure is available (1977 - 1996). We find that the price level sharply increases during the first two quarters and after roughly one year has returned to its original level after which it

Average bank responses. Figure 6 reports the behavior of the three loan components during a monetary and a non-monetary downturn using the series for all banks. The graph shows that there are important differences between the behavior of the three loan series after a monetary tightening. Both real estate loans and consumer loans display sharp negative decreases, although there is some delay before both begin to fall. In contrast, C&I loans immediately increase and are significantly positive for several years. Den Haan, Sumner, and Yamashiro (2007) provide arguments related to hedging and banks safeguarding their capital adequacy ratio that can explain these movements. Here we take the responses as given and analyze what they imply for the response of total loans.

The responses of the loan components during a non-monetary downturn gives a very different picture. First, real estate loans decrease, but it is not a statistically significant decrease and the decrease is less than the one observed during a monetary during a monetary downturn. Consumer loans are little changed in response to output shocks. Thus, the behavior of real estate and consumer loans is consistent with the view that a monetary tightening reduces the supply of bank loans by more than is predicted by the decline in real activity. In contrast, C&I loans decrease during a non-monetary downturn.

Responses for small and large banks. In Figures 7 and 8 we plot the responses of the three loan components for large banks (top 10 percentile) and small banks (bottom 90 percentile).[22] In Section 3.1, we showed that there were substantial differences in the time-series behavior of the loan series for small and large banks and that the relative importance of large banks had grown over time. Given these differences it is remarkable that the behavior of the loan components during both a monetary and a non-monetary

hovers around zero. Although not a solution to the price puzzle it is an improvement, since the price level displays a persistent increase to a monetary tightening when innovations in the federal funds rate are used as the monetary policy shock. More importantly, our other results are robust when alternative VAR specifications are used to obtain different price responses.

[22] When we replace the loan components with those of small or large banks, we find that the responses for output, the federal funds rate, and the price level are similar to those in Figure 5 and are not reported.

downturn are so similar for the two types of banks.[23] In particular, for both large and small banks we observe that the responses for real estate and consumer loans decrease during a monetary downturn, and not (or less) during a non-monetary downturn. Similarly, C&I loans increase during a monetary downturn and decrease during a non-monetary downturn. There are some intriguing quantitative differences, however. For example, the response of real estate loans is larger for small banks than it is for large banks. The opposite is true for consumer loans.

5 Implied time-varying total loans responses

In Section 2, we showed that the impulse response function of a variable that is the sum of variables in a VAR will, in general, be time varying. We can expect this to be more of an issue when (i) the responses of the micro components differ and (ii) their relative magnitudes change over time. In Section 3.1, we showed that the relative magnitudes of loan components changed substantially over time both for large and for small banks and in Section 4 we documented that C&I loans respond quite differently to monetary policy shocks than real estate and consumer loans.

To see how important the variation in initial conditions across the sample is, we calculate the impulse response function for total loans for all observed initial values of the loan components. The results are plotted in Figures 9, 10, and 11 for all banks, large banks, and small banks, respectively. In each figure, Panel A plots the response of total loans to a shock in the federal funds rate and Panel B plots the difference between the response of total loans during a monetary downturn and a non-monetary downturn. The figures show that there is indeed substantial variation in the response of total loans, especially for large banks and especially for the series that measures the difference between the monetary and the non-monetary downturn.

The top panel of Figure 9 shows that the total loan responses for all banks are, at first,

[23] Kashyap and Stein (1995) find more substantial differences between the responses for large and small banks in their specifications that do not control for changes in real activity. When they do control for changes in real activity the differences are strongly reduced.

always positive, then always turn negative, but the negative responses last at most three years and for some initial conditions not even one year. The results in the bottom panel correct the loan responses for the reduction in economic activity and show that there are now numerous initial conditions for which the plotted loan response is always positive, although there are also initial conditions for which the responses are negative for several periods.

The results for large banks are very similar to those of all banks, although for large banks there are some initial conditions for which the plotted loan responses are always positive.

For small banks the responses are (at least in the first three years) consistently negative and below those found for large banks.[24] This is true both when the responses are and when they are not corrected for the reduction in economic activity. Nevertheless, even for small banks we find important quantitative differences. In particular, for the 8th period response the largest decrease of 0.476% is more than twice as large as the smallest decrease of 0.238%.

Whereas the responses of the loan components displayed robust and significant responses to a monetary tightening (but not in the same direction), the responses of total loans—with the exception of the response for small banks—hover around zero in the first couple of years. So, to some extent, the responses of total loans give a very incomplete picture of what happens to bank lending during a monetary tightening.

We also compared the responses of total loans discussed above, which are based on a VAR with loan components, with the response of total loans that are based on a VAR that does not disaggregate total loans into its components. Of course, the response of total loans from the latter would not be time varying. We find that for small banks the response of total loans is similar to the average of the time-varying responses. For the large bank and all banks series, however, the response is a bit above the time-varying responses.[25]

[24] This is consistent with the results of Kashyap and Stein (1995) and Kishan and Opiela (2000).

[25] Given that the impulse responses of the loan components are actually estimated fairly precisely, the reason is likely to be that the simple VAR, without loan components, has a hard time capturing the dynamics of the system with only a relatively small number of lags.

The figures discussed above do not make clear which impulse response function corresponds to what set of initial conditions. In Figure 12 we make this clear by plotting the response eight quarters after the shock using as initial conditions the observed values of the loan components in the period indicated on the x-axis. The patterns are similar for both small and large banks. But as mentioned above, the response for small banks is below the response for large banks. We can expect the response of an aggregate variable to decrease over time if the variable with the response that is less negative becomes smaller over time. That is true in our case since the fraction of C&I loans has decreased over time and the response of C&I loans is, not only, less negative, it is positive. We see that the responses for total loans indeed decrease over time although the results are not monotone. The eight-quarter responses for total loans increase in the beginning of the sample and reaches its maximum in the early eighties before a steady decline sets in. For small banks the smallest value is observed in the early nineties after which the results stabilize. For large banks a minor increase is observed during the nineties. To analyze the statistical significance of the amount of time variation we checked whether the difference between the response observed in the first quarter of 1983 (when the most positive value for large banks is observed) and the response in the last quarter of the sample is significantly different from zero. For all three loans series we find that the difference is significant at the 5% level.[26]

6 Time-varying total loans responses

Figure 12 predicts a particular pattern for the response of total bank loans to a monetary tightening. There are basically two u-shaped patterns with the responses reaching a maximum around 1983, which is exactly when the share of C&I loans, that have a positive response, reaches its highest value. The question arises whether one would find something similar if one would try to directly estimate the response of total loans using a methodology that allows the response to be time varying. The problem is that there are several

[26] In each Monte Carlo replication of our bootstrap procedure we calculated this difference and we checked whether the 5% percentile was positive.

ways to do this, for example, Bayesian VARs with time-varying coefficients or standard VARs using rolling samples. The problem is enhanced by the fact that numerous choices have to be made in implementing these techniques. The implied responses for total loans documented in Figures 9 through 12 are based on a snapshot, i.e., what the total loans responses are for the initial conditions observed in one particular period. Consequently, with direct estimation the sample period should be quite small, but this would make it difficult to precisely estimate the many parameters in the VAR.

Despite all these caveats, it would be interesting to see whether there is at least some correspondence between the implied time-varying total loan responses and those found by direct estimation. To investigate whether the directly estimated total loans response is time varying, we use relatively short rolling samples. Using short samples means that we have to make several changes to safeguard the degrees of freedom. Most importantly, we focus on the monthly H.8 loan data. These data are of lesser quality than the Call Report data, but are available on a monthly frequency increasing the degrees of freedom.[27]

Another aspect to keep in mind is that the responses of the loan components are, of course, also changing, especially if they are estimated with short rolling windows. To see whether the changes in the relative magnitudes of the loan components play a role in explaining the changes in the directly estimated total loan responses, we do the following.

In each sample, we estimate the 10^{th}-quarter (i.e., 30^{th}-month) total loan response. Next, we estimate the 10^{th}-quarter loan component responses and construct an indirect estimate of the 10^{th}-quarter total loan response by taking the weighted sum of the loan component responses. The weights used are *fixed* averages, equal to the observed averages over the whole sample.

In the figures, we plot the difference between the directly estimated and the constructed total loan response. The constructed total loan response does not take into account the source of time variation emphasized in this paper, namely changing relative magnitudes of the components. So the question is whether the plotted difference can be explained by

[27] See Den Haan, Sumner, and Yamashiro (2002) for a comparison of H8 and Call Report data. We also exclude the price index from the VAR to increase the degrees of freedom. We did not find this to affect the results.

the changing weights. To answer this question, we plot in the figures also the 10^{th}-quarter response constructed using time-varying weights and *fixed* loan component responses.[28] For the fixed loan component impulse response function, we use the average across the rolling windows.

Figure 13 reports the results for the total loans responses during a monetary tightening and figure 14 reports the results for the difference between the responses during a monetary and a non-monetary downturn. The top panel in each graph shows the results for rolling windows of 25 years and the bottom panel shows the results for rolling windows of 30 years.

In all four cases, there is a general tendency for the changes in the total loan response predicted using only changes in the weights (the dotted line) to move together with the changes in the total loan response that are not explained by changes in the responses of the components themselves (the solid line). More than a general comovement was not to be expected. The weights change relatively slowly. Consequently, the changes in the total loan response due to changes in the weights occur gradually. In contrast, the counterpart is obtained using rolling windows and is, thus, subject to quite a bit of sampling variation.[29]

7 Concluding Comments

The time-varying responses for *total* bank loans reported in this paper are from a VAR with constant coefficients. The question arises as to whether the coefficients of the VAR remain the same when the relative magnitudes of the loan components display such substantial changes.[30] It is even a possibility that banks behave in such a way to keep the response of total loans to monetary policy shocks constant when the relative magnitude of the loan

[28] Also, the mean is taken out to make the difference between the two total loans responses comparable to the predicted level response.

[29] For this reason, one should not take this exercise too seriously. The results only look nice for a certain sample length. If the length of the rolling windows becomes too short, then the estimates are very volatile. If the lengths become too long, then there is no variation left to explain. We have no argument for choosing the adopted window lengths other than that these generate the desired general comovement.

[30] The VAR does include a deterministic trend term, but this only captures changes in the constant term.

components change. In this case, it might be better to actually use a VAR that only includes total loans.

Obviously one always has to be aware of the possibility that behavior changes over time. The main point of this paper is that impulse response functions of aggregated variables can change over time *even if* the behavior of the micro components does not change over time. In this paper we have demonstrated that this is a quantitatively important phenomenon for total loans.

A Data sources

The Call Report bank balance-sheet data are available online.[31] Also, a description on how they are constructed can be found in Den Haan, Sumner, and Yamashiro (2002). In this paper we use the "level series".

Quarterly observations for the CPI and federal funds rate are constructed by taking an average of the monthly observations downloaded from http://research.stlouisfed.org (CPI) and http://www.federalreserve.gov (federal funds rate). The quarterly income variable used is earnings (by place of work) from the Bureau of Economic Analysis. It was downloaded from http://www.bea.doc.gov/. In related work we examine the effect of regional responses to monetary policy shocks and the advantage of this real activity measure is that it is available at the regional level. The results are very similar, however, if we use GDP and its deflator.

The monthly data used in Section 6 are the H.8 bank loan data. These are downloaded from http://www.federalreserve.gov. The industrial production data are downloaded from http://research.stlouisfed.org.

References

Barth, M. J. I., and V. A. Ramey (2001): "The Cost Channel of Monetary Transmission," *NBER Macroeconomics Annual*, 16, 199–256.

[31] At http://www1.feb.uva.nl/mint/wdenhaan/data.htm

Bernanke, B. S., and A. S. Blinder (1992): "The Federal Funds Rate and the Channels of Monetary Transmission," *American Economic Review*, 82, 901–921.

Bernanke, B. S., and C. S. Lown (1991): "The Credit Crunch," *Brookings Papers on Economic Activity*, 2, 204–239.

Christiano, L. J., M. Eichenbaum, and C. L. Evans (1999): "Monetary Policy Shocks: What Have We Learned and to What End?," in *Handbook of Macroeconomics*, ed. by J. B. Taylor, and M. Woodford, pp. 65–148. North-Holland, Amsterdam.

Den Haan, W. J., S. W. Sumner, and G. Yamashiro (2002): "Construction of Aggregate and Regional Bank Data Using the Call Reports: Data Manual," Unpublished manuscript, University of Amsterdam.

——— (2007): "Bank Loan Portfolios and the Monetary Transmission Mechanism," *Journal of Monetary Economics*, 54, 904–924.

——— (2009): "Bank Loan Portfolios and the Canadian Monetary Transmission Mechanism," *Canadian Journal of Economics*, 42, 1150–1175.

Gertler, M., and S. Gilchrist (1993): "The Cyclical Behavior of Short-Term Business Lending: Implications for Financial Propagation Mechanisms," *European Economic Review*, 37, 623–631.

Giordani, P. (2004): "An Alternative Explanation of the Price Puzzle," *Journal of Monetary Economics*, 51, 1271–1296.

Granger, C. W. (1980): "Long Memory Relationships and the Aggregation of Dynamic Models," *Journal of Econometrics*, 14, 227–238.

Kashyap, A. K., and J. C. Stein (1995): "The Impact of Montetary Policy on Bank Balance Sheets," *Carnegie-Rochester Series on Public Policy*, 42, 151–195.

Kishan, R., and T. Opiela (2000): "Bank Size, Bank Capital, and the Bank Lending Channel," *Journal of Money, Credit and Banking*, 32, 121–141.

Pesaran, M. H. (2003): "Aggregation of Linear Dynamic Models: An Application to Life-Cycle Consumption Models under Habit Formation," *Economic Modelling*, 20, 383–415.

Pesaran, M. H., R. G. Pierse, and M. S. Kumar (1989): "Econometric Analysis of Aggregation in the Context of Linear Prediction Models," *Econometrica*, 57, 861–888.

Potter, S. (1999): "Nonlinear Time Series Modelling: An Introduction," *Journal of Economic Surveys*, 13, 505–528.

Romer, C. D., and D. H. Romer (2004): "A New Measure of Monetary Shocks: Derivation and Implications," *American Economics Review*, 94, 1055–1084.

Rudebusch, G. D. (1998): "Do Measures of Monetary Policy in a VAR Make Sense?," *International Economic Review*, 39, 907–931.

van Garderen, K. J., K. Lee, and M. H. Pesaran (2000): "Cross-Sectional Aggregation of Non-Linear Models," *Journal of Econometrics*, 95, 285–331.

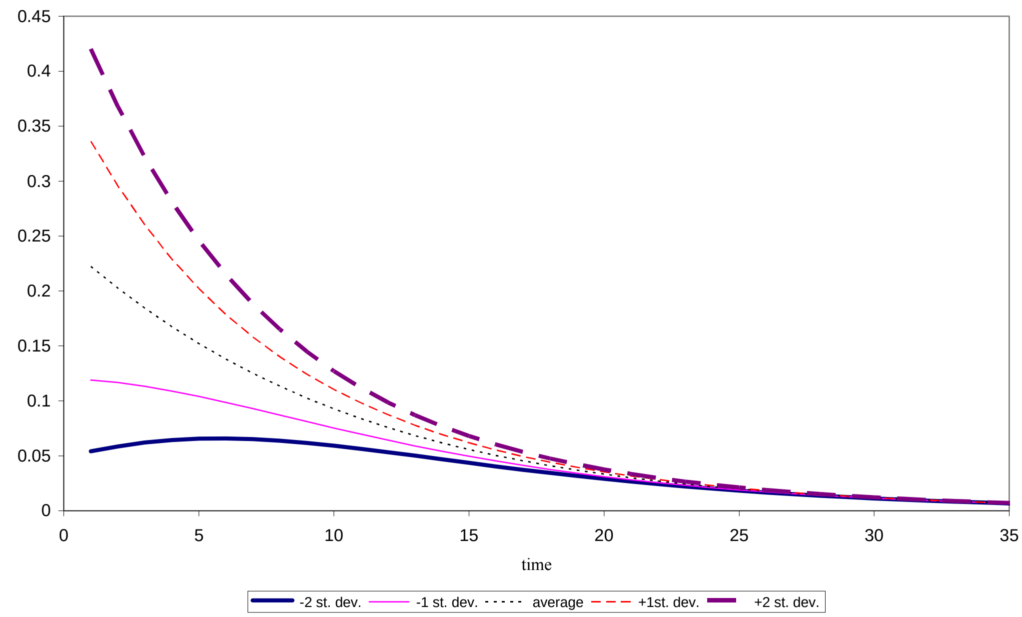
Table 1: Increased importance of large banks

	1977Q1		2000Q4	
	large banks	small banks	large banks	small banks
C&I	83%	17%	91%	9%
real estate	67%	33%	82%	18%
consumer	65%	35%	89%	11%

Table 2: Summary statistics for growth rates

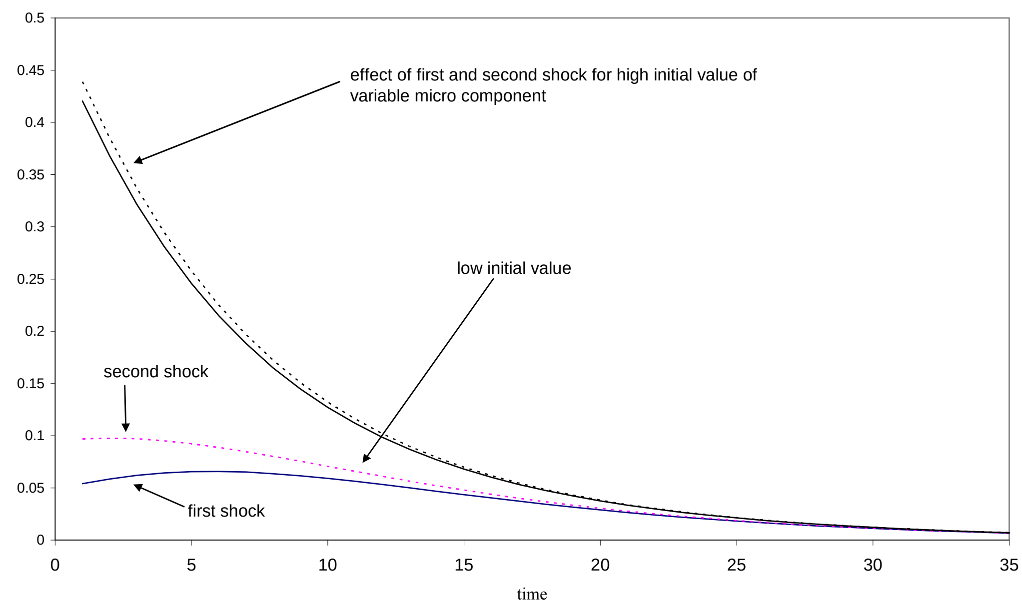
	C&I		real estate		consumer	
	large	small	large	small	large	small
average	1.74%	1.06%	2.68%	1.87%	1.91%	0.32%
standard deviation	2.44%	2.07%	1.57%	1.31%	2.88%	2.07%
autocorrelation	0.20	0.52	0.55	0.63	0.26	0.44

Figure 1: Impulse response function of z_t for different initial values of $\ln(z_{1,t}/ z_{2,t})$



Note: This graph plots the impulse response function of $\ln(z_t)$ in response to a one-standard-deviation shock in e when the initial value of $\ln(z_{1,t}/ z_{2,t})$ varies from being two standard deviations below to two standard deviations above its average value (of zero)

Figure 2: Impulse response function of z_t for first and second shock

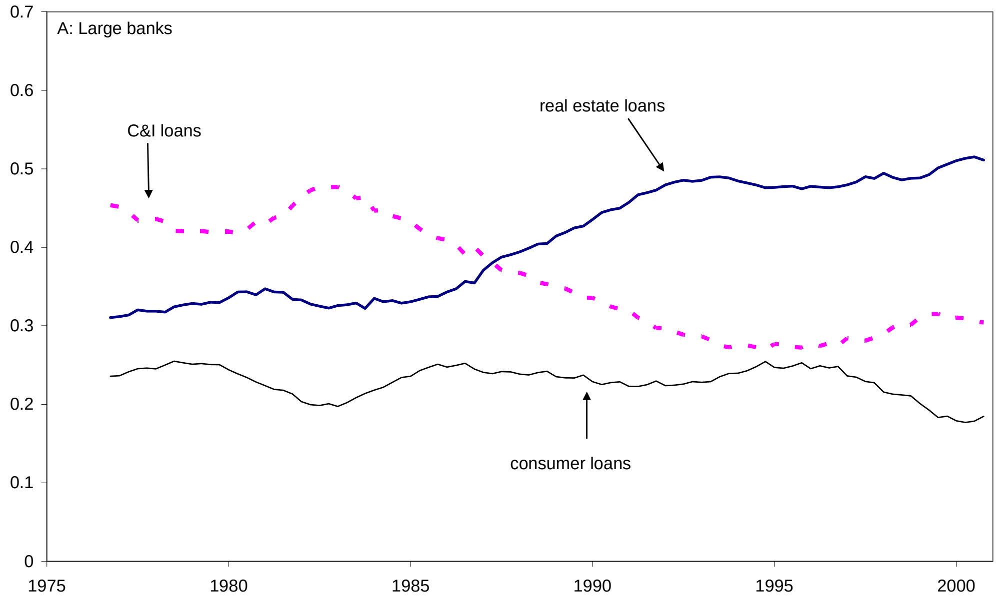


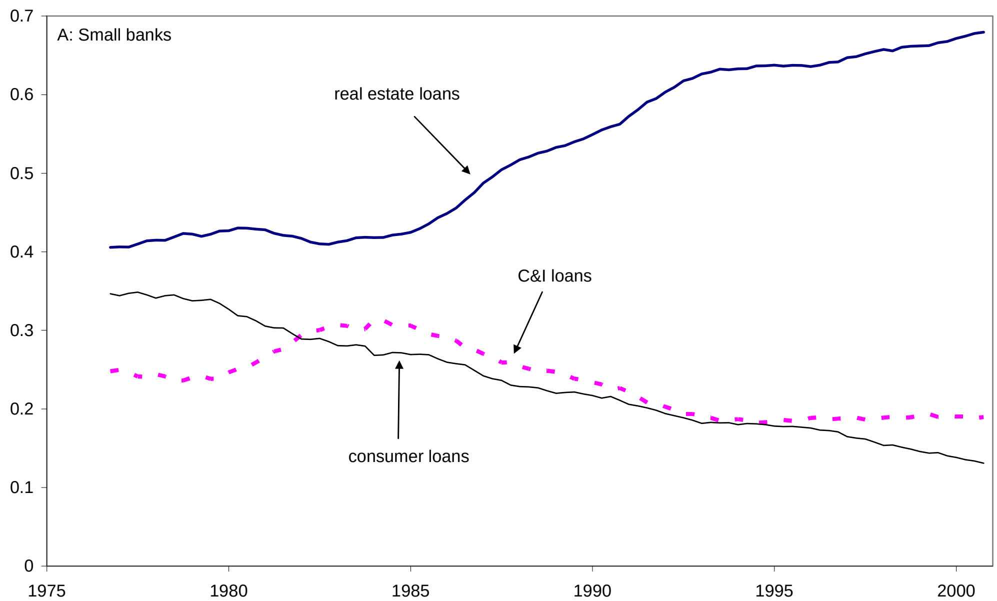
Note: This graph plots the impulse response function of $\ln(z_t)$ in response to a one-standard-deviation shock in e (solid line) and the impulse response function of $\ln(z_t)$ in response to a subsequent shock of equal magnitude (dashed line) when the value of $\ln(z_{1,t}/ z_{2,t})$ at the time of the first shock occurs is equal to two standard deviations below and two standard deviations above its average value.

Figure 3: Loan components for large and small banks

Note: These graphs plot for each quarter the natural log growth rate over the past year.

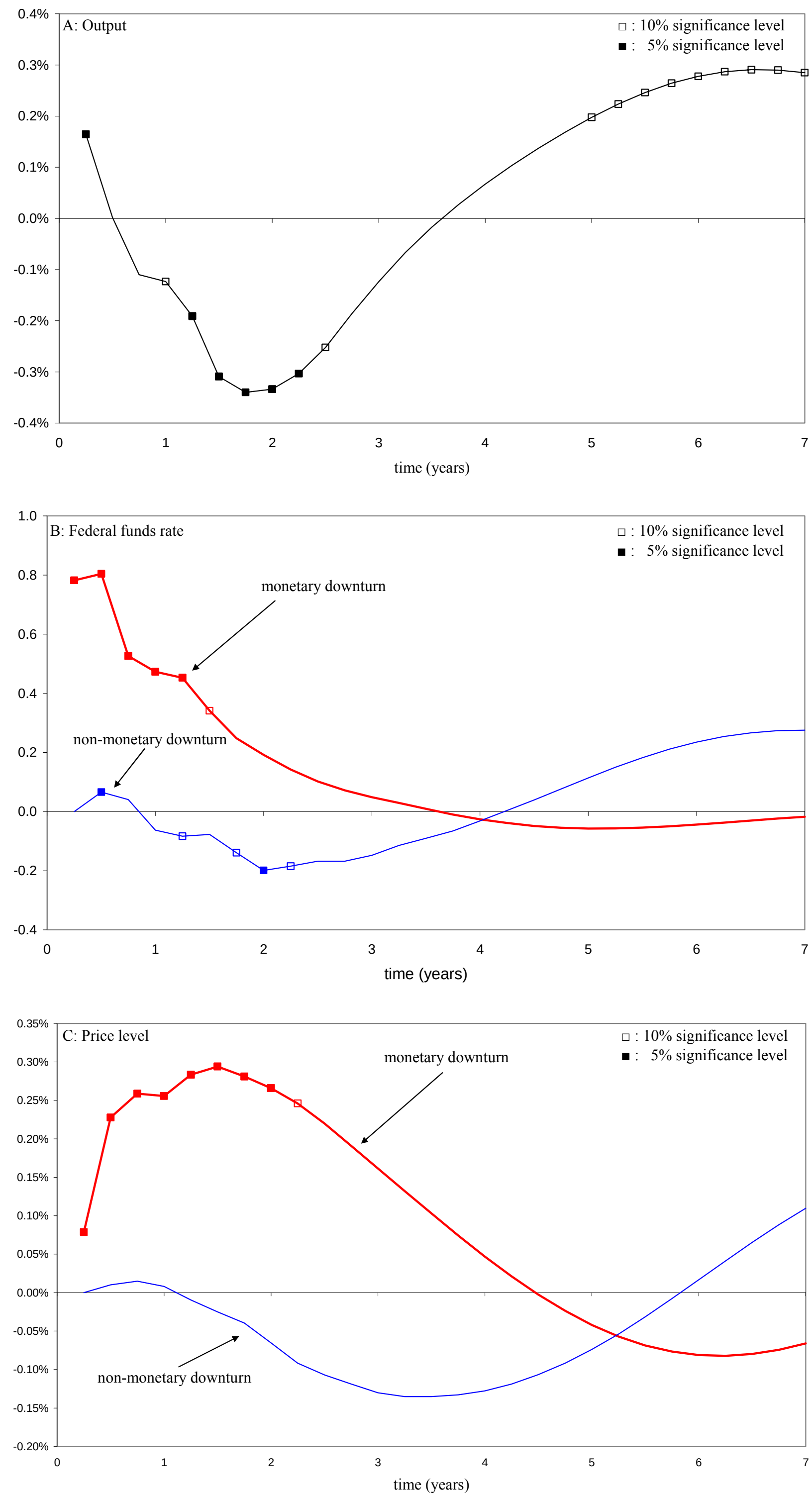
Figure 4: Banks' loan portfolio





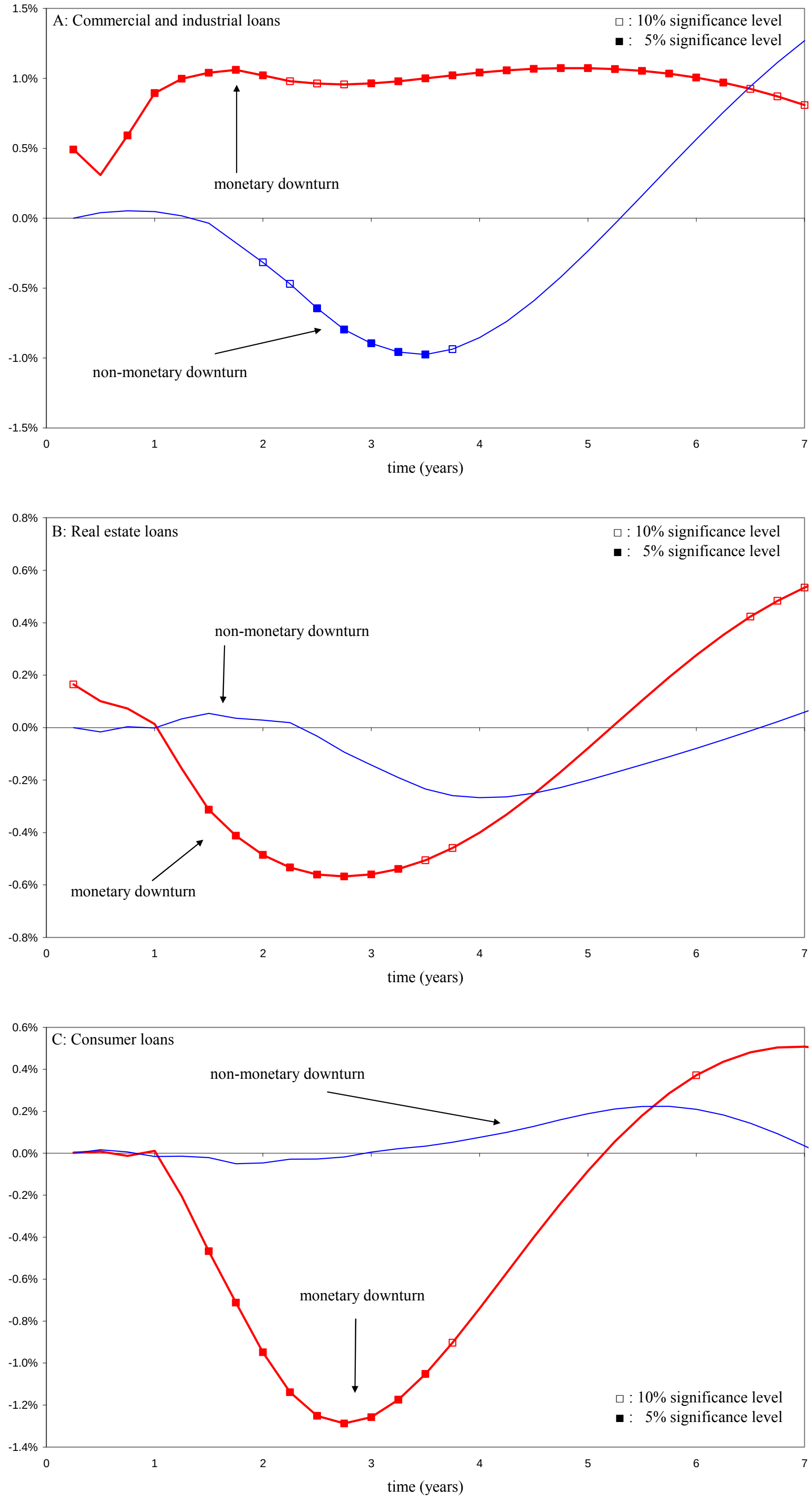
Note: These graphs plot the share of the indicated loan component as a fraction of the sum of the three loan components.

Figure 5: Impulse responses for output, price level, and federal funds rate
(VAR with “all bank” loan series)



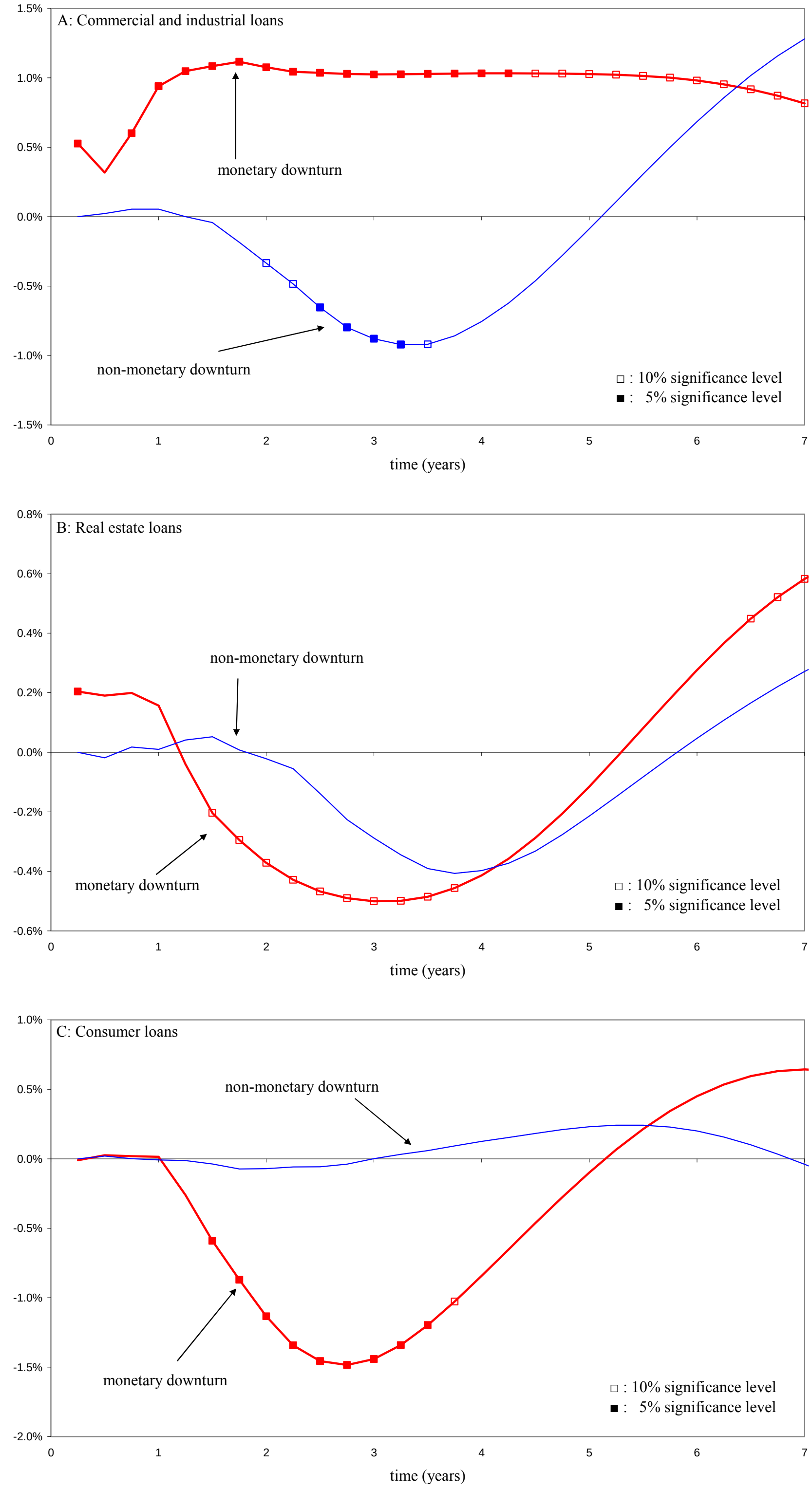
Note: These graphs plot the response of the indicated variable to a one-standard deviation federal funds rate shock, i.e., a monetary downturn. In Panels B and C the curve labelled “non-monetary downturn” plots the time path of the federal funds rate and consumer price index following a sequence of output shocks that generates a time path for output that is identical to that of the monetary downturn plotted in panel A. The results are based on the benchmark specification. Open squares indicate a significant response at the 10% level and a solid square indicates a significant response at the 5% level (both one-sided tests).

Figure 6: Loan impulse responses - All banks



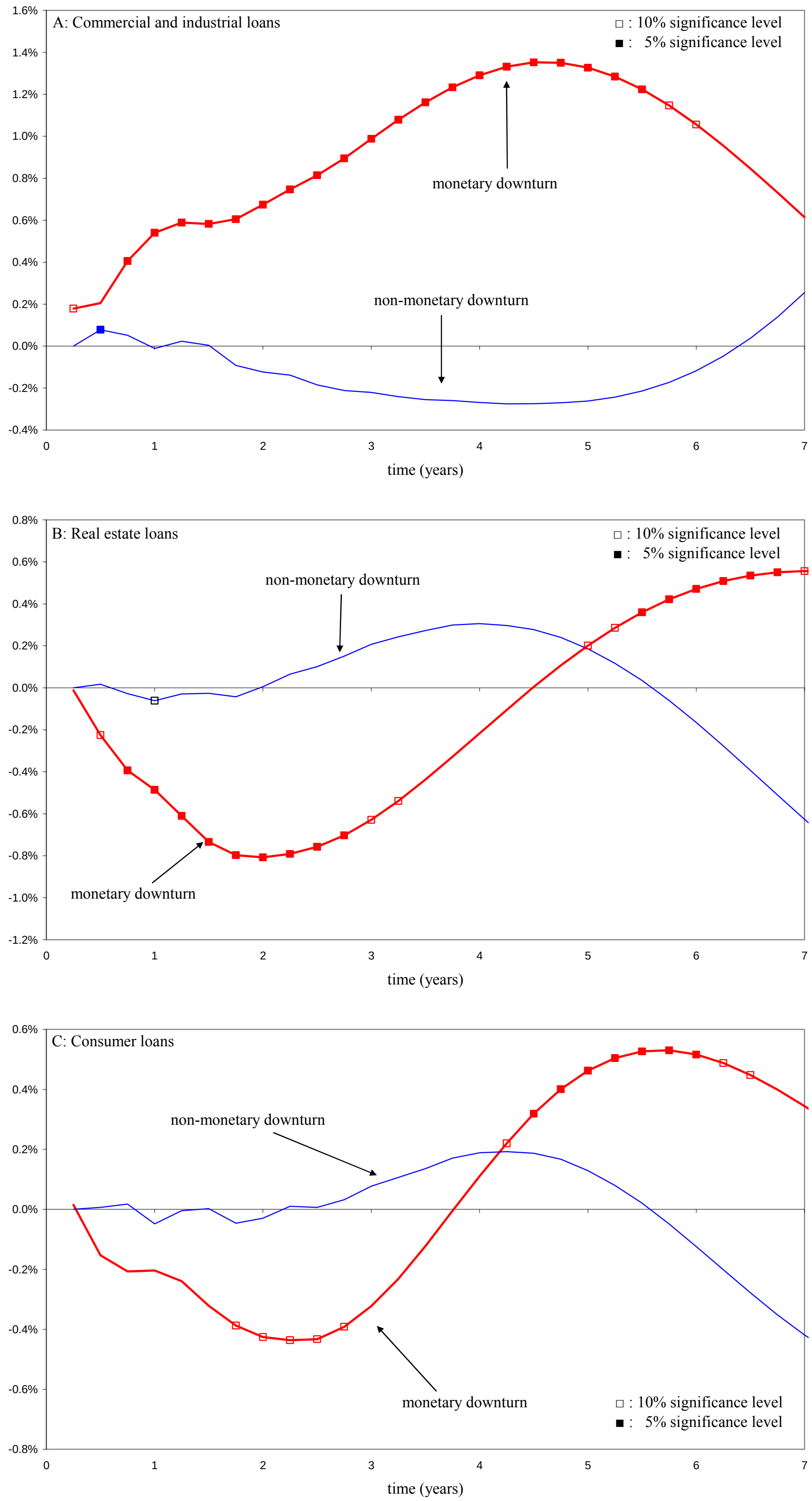
Note: These graphs plot the response of the indicated loan variable to a one-standard deviation federal funds rate shock, i.e., a monetary downturn. The curves labelled “non-monetary downturn” plot the time path of the loan variable following a sequence of output shocks that generates a time path for output that is identical to that of the monetary downturn (plotted in panel A of Figure 4.1). The results are based on the benchmark specification. Open squares indicate a significant response at the 10% level and a solid square indicates a significant response at the 5% level (both one-sided tests).

Figure 7: Loan impulse responses - Large banks



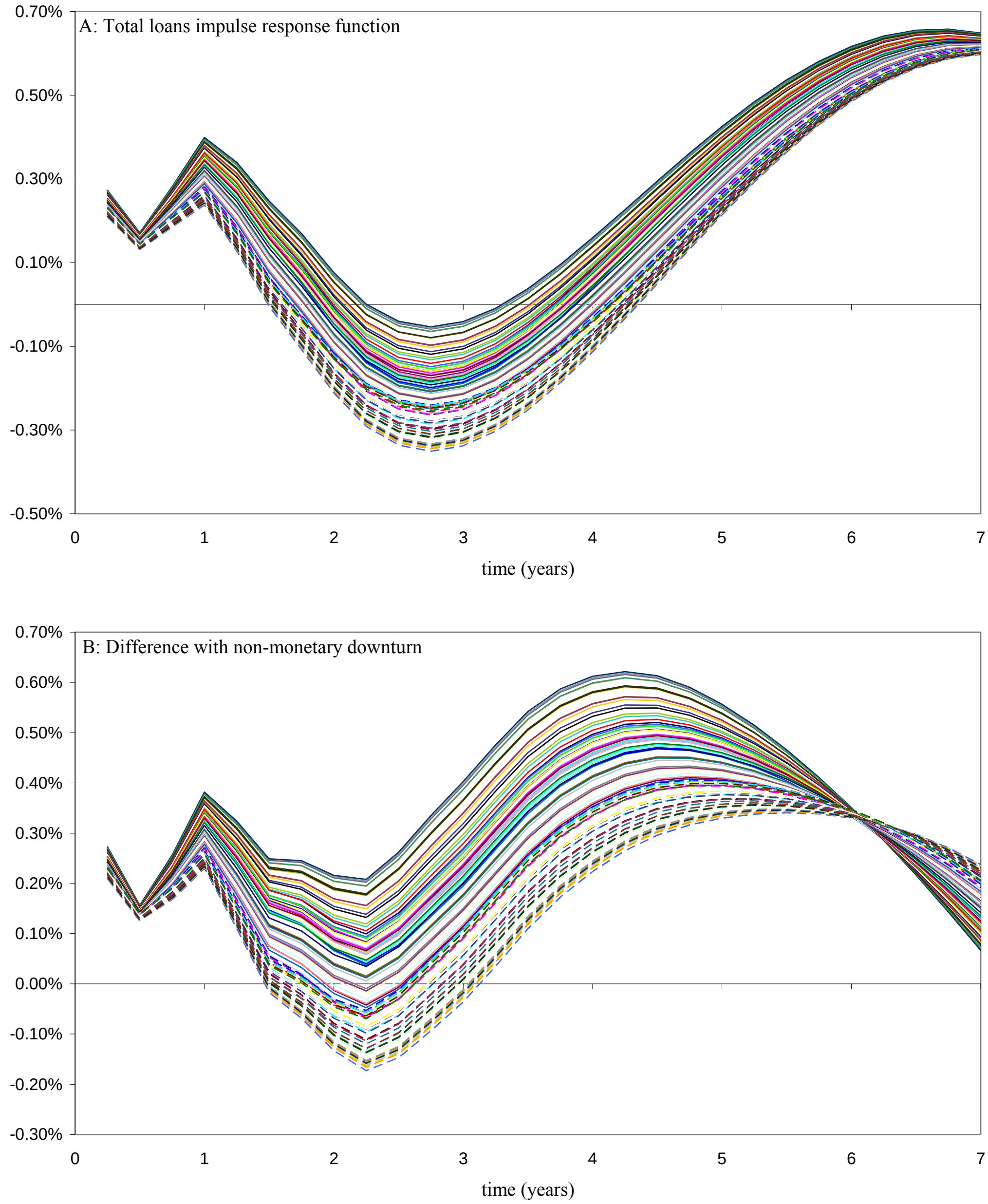
Note: These graphs plot the response of the indicated loan variable to a one-standard deviation federal funds rate shock, i.e., a monetary downturn. The curves labelled "non-monetary downturn" plot the time path of the loan variable following a sequence of output shocks that generates a time path for output that is identical to that of the monetary downturn. The results are based on the benchmark specification. Open squares indicate a significant response at the 10% level and a solid square indicates a significant response at the 5% level (both one-sided tests).

Figure 8: Loan impulse responses - Small banks



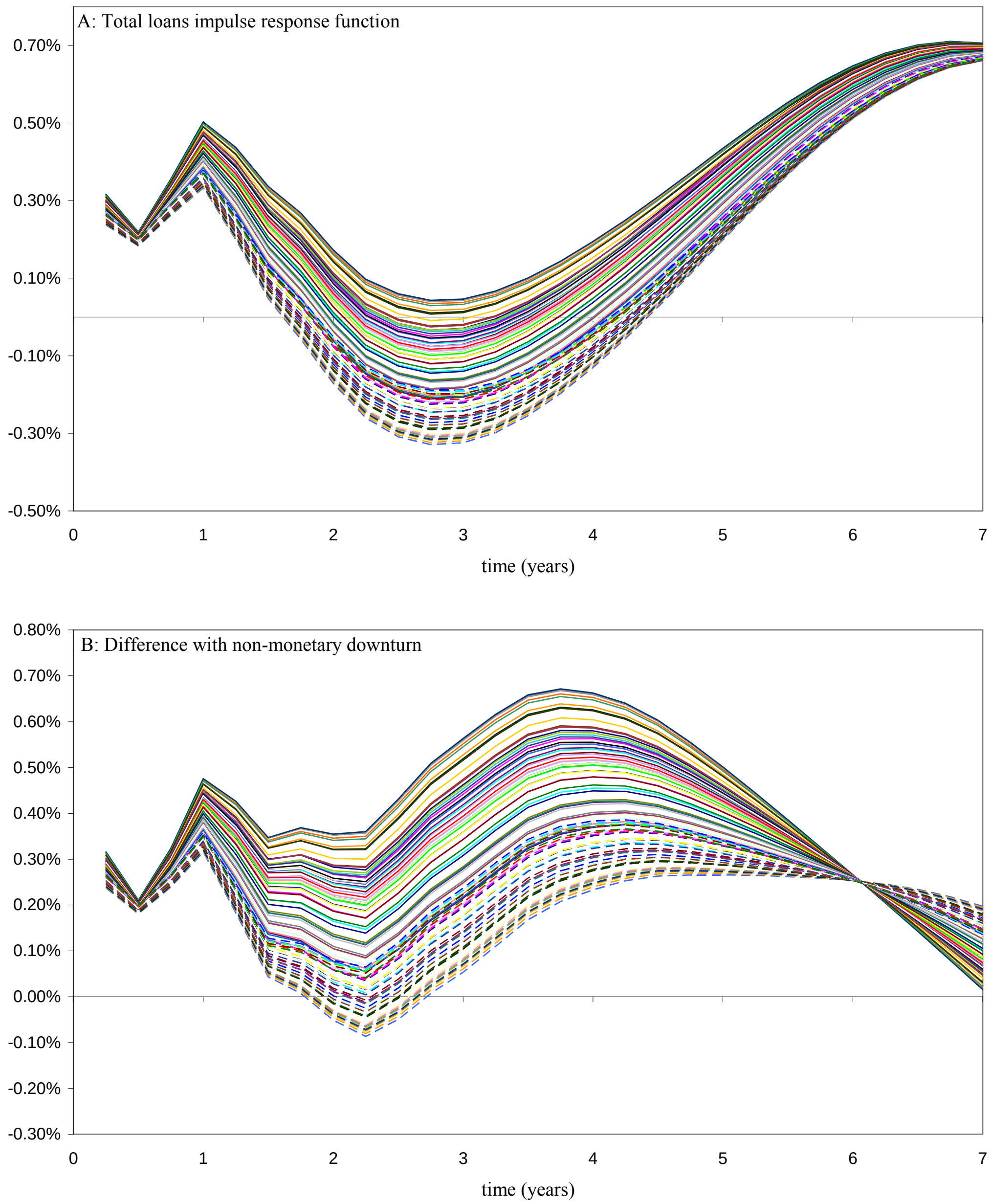
Note: These graphs plot the response of the indicated loan variable to a one-standard deviation federal funds rate shock, i.e., a monetary downturn. The curves labelled "non-monetary downturn" plot the time path of the loan variable following a sequence of output shocks that generates a time path for output that is identical to that of the monetary downturn. The results are based on the benchmark specification. Open squares indicate a significant response at the 10% level and a solid square indicates a significant response at the 5% level (both one-sided tests).

Figure 9: Implied total loans impulses for VAR with loan components - All banks



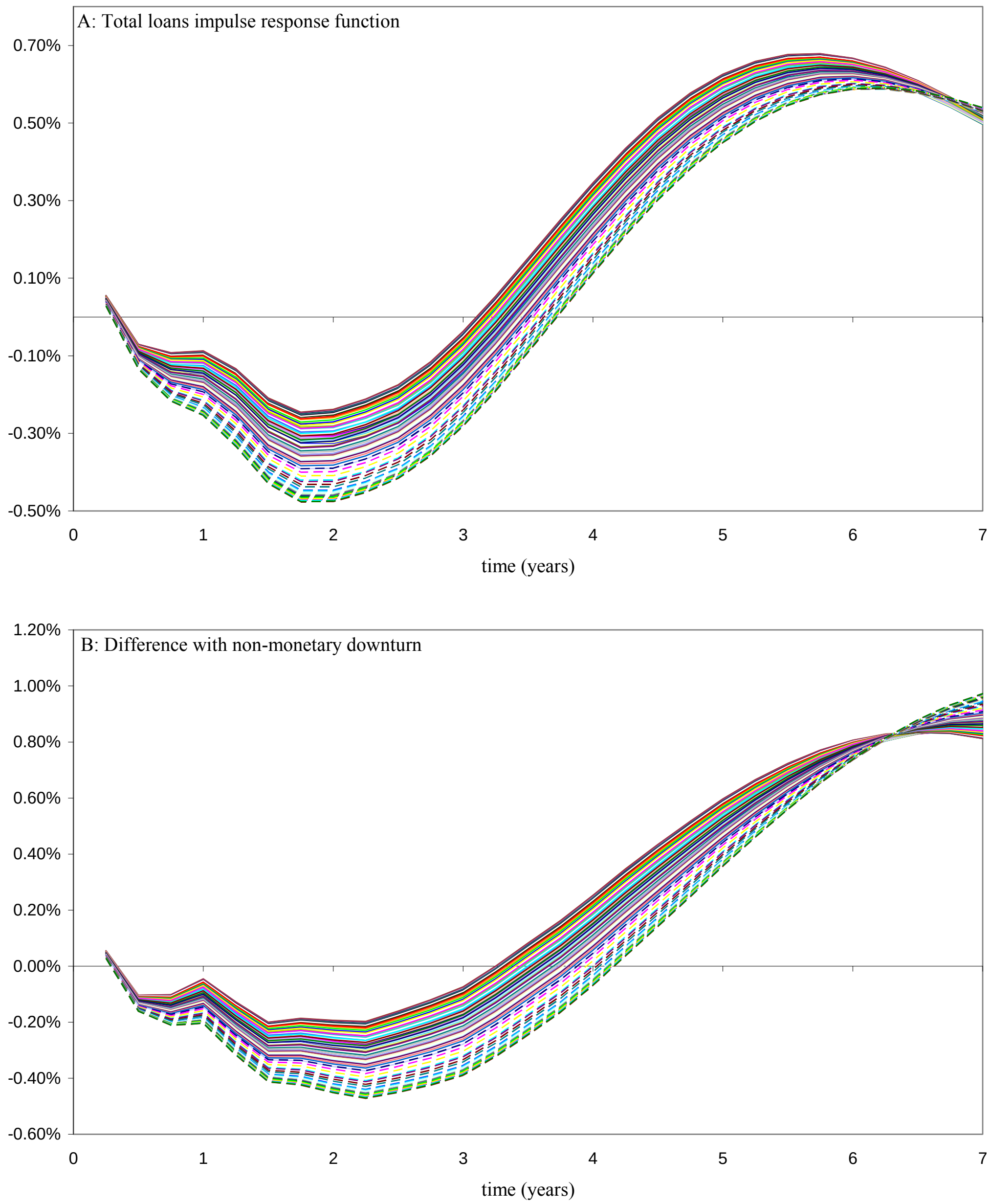
Note: Panel A plots the impulse response function of total loans for all initial conditions observed in the sample. Panel B plots the difference between the response of total loans during a monetary downturn and a non-monetary downturn.

Figure 10: Implied total loans impulses for VAR with loan components - Large banks



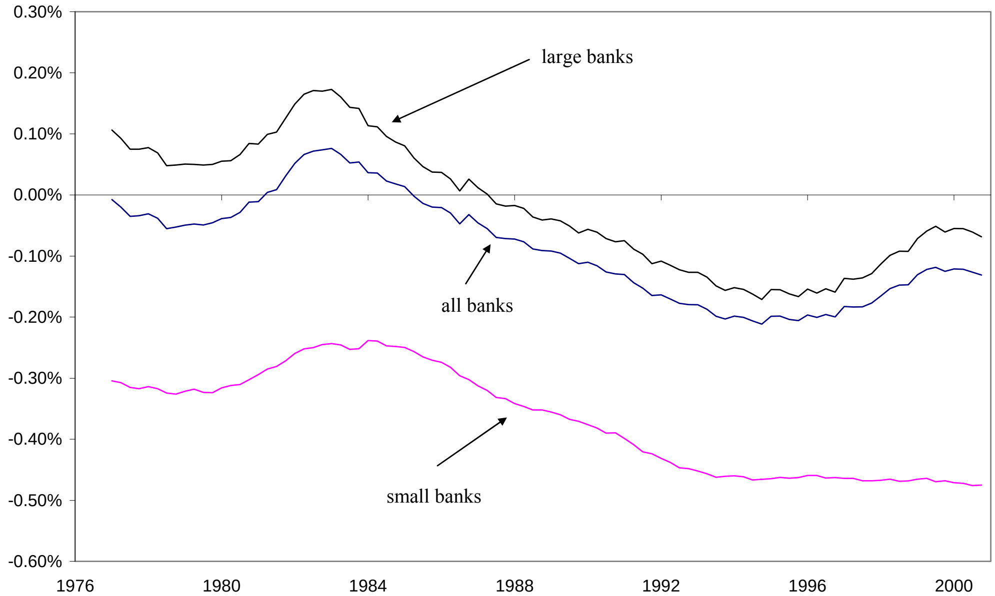
Note: Panel A plots the impulse response function of total loans for all initial conditions observed in the sample. Panel B plots the difference between the response of total loans during a monetary downturn and a non-monetary downturn.

Figure 11: Implied total loans impulses for VAR with loan components - Small banks



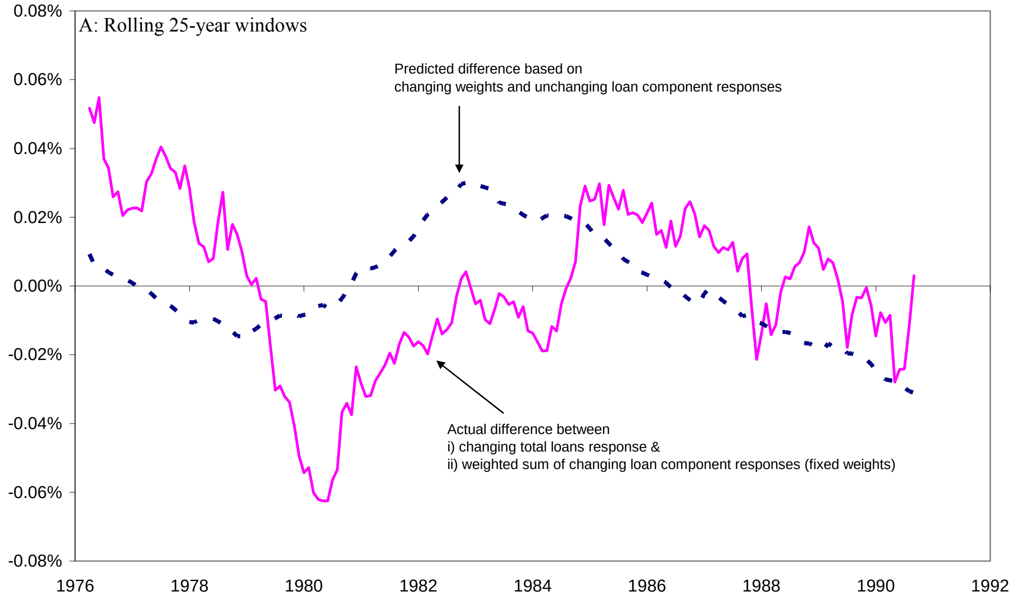
Note: Panel A plots the impulse response function of total loans for all initial conditions observed in the sample. Panel B plots the difference between the response of total loans during a monetary downturn and a non-monetary downturn.

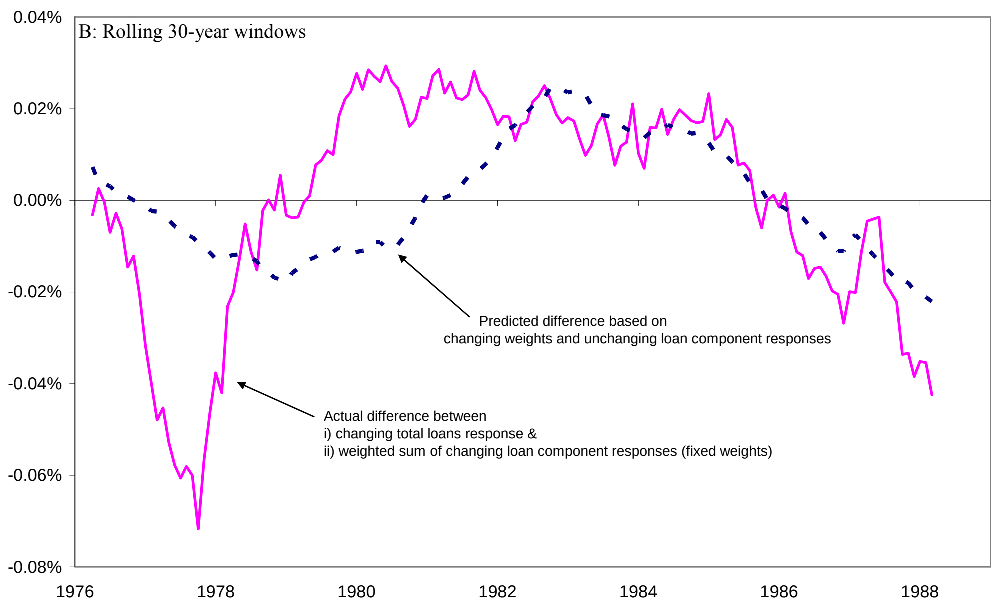
Figure 12: 8th-quarter implied total bank loans response for VAR



Note: This graph plots the 8th-quarter impulse response of indicated total loans series using as initial values those observed in the period indicated on the x-axis.

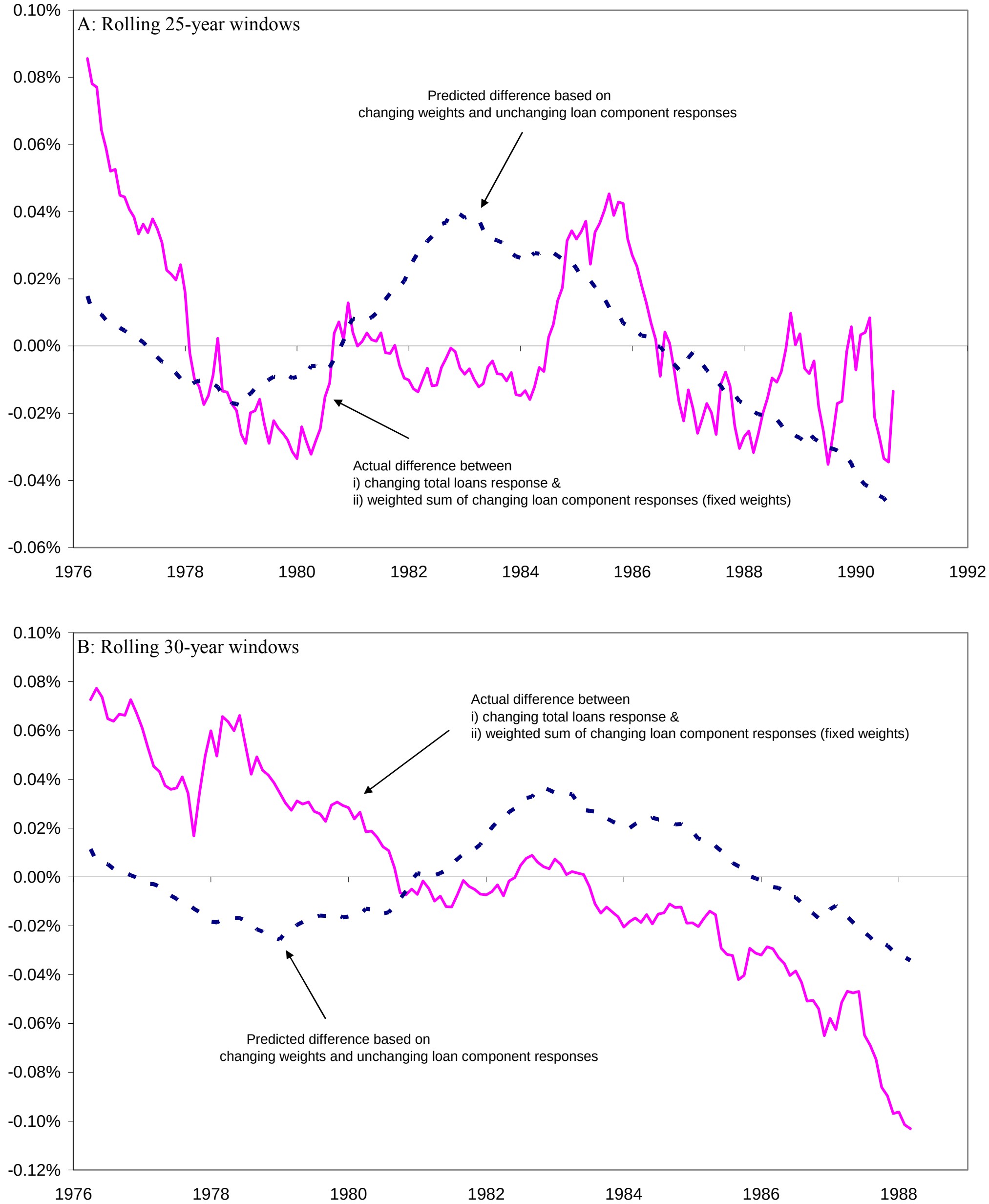
Figure 13: Variation of total loan responses explained by changing weights – H.8 data (Responses to monetary policy shock)





Note: The solid lines represent the difference between the 10th-quarter impulse total loans response directly estimated and the indirectly calculated response using the weighted sum of the responses of the loan components using <u>fixed</u> weights. All responses are estimated using rolling windows with the value on the x-axis at the midpoint of the sample. The dotted line represents the weighted sum of the (fixed) average loan component responses and <u>time-varying</u> weights.

Figure 14: Variation of total loan responses explained by changing weights – H.8 data (Difference between responses during a monetary and non-monetary downturn)



Note: The solid lines represent the difference between the 10th-quarter impulse total loans response directly estimated and the indirectly calculated response using the weighted sum of the responses of the loan components using fixed weights. All responses are estimated using rolling windows with the value on the x-axis at the midpoint of the sample. The dotted line represents the weighted sum of the (fixed) average loan component responses and time-varying weights.