Quantifying the Monetary Transmission Mechanism: A Mixed-Frequency Factor-Augmented Vector Autoregressive Regression Approach

Zhi Zhao

University of Califonia, Riverside

Abstract

This paper studies the monetary transmission mechanism in the U.S. It proposes a mixed-frequency version of the factor-augmented vector autoregressive regression (FAVAR) model, which is used to construct a coincident index to measure the monetary transmission mechanism. The model divides the transmission of changes in monetary policy to the economy into three stages according to the timing and order of the impact. Indicators of each stage are measured and identified using different data frequencies: fast-moving variables (stage 1, asset returns at the weekly frequency), intermediate moving variables (stage 2, credit market data at the monthly frequency), and slow-moving variables (stage 3, macroeconomic variables at the quarterly frequency). The resulting coincident index exhibits leading signal for all recessions in the sample period and provides implications on the dynamics of the monetary transmission mechanism. The proposed coincident index also indicates that monetary transmission mechanism is changing over time.

JEL Classification numbers: C32, C43, E52

Keywords: monetary transmission mechanism, mixed-frequency, FAVAR, coincident index.

I. Introduction

Monetary transmission mechanism describes how monetary policy shock affects real variables in the economy such as aggregate output and employment rate. As monetary policy impacts many real variables in the economy in the short run, it is important for policy makers to have an assessment of the timing and scale of such effects. This requires understanding of the underlying connections between monetary policy and real variables. However, there exist many channels through which the monetary transmission mechanism takes place, which makes it a more complex and yet enticing research question.

There is a growing literature, both theoretical and empirical, which aims to unveil the underlying channels of the monetary transmission mechanism. Theoretically, the traditional view of monetary transmission mechanism is known as the interest rate channel, in which investors adjust their assets according to changes in interest rate (Tobin 1969). Another view of the monetary transmission mechanism is through the credit channel, related to the amplification effect of changes in interest rate on loan supply in credit markets (Bernanke and Gertler 1989). The credit channel view is built on the assumption that the credit market is imperfect because of government intervention, asymmetric information, and agency problems. The credit channel can be further divided into two mechanisms: bank lending channel and firm balance sheet channel. In the bank lending channel, banks play an important and unique role as they are the only source of finance for certain borrowers who have no access to the credit market, such as small firms. The balance sheet channel, on the other hand, refers to the direct effect of interest rate changes on agents' ability to borrow due to changes in asset value and profitability.

While the credit channels focus on the supply side of the credit market, there are also the risk-taking channel, which is related to the demand side of the credit market. Nicolo et al. (2010) discuss three different risk-taking channels through which expansionary monetary policy could lead to risk-taking behavior. The first channel is that banks have incentive to substitute low yield safe asset with high yield riskier asset. The second channel is through a "search for yield," that is, low interest rate gives financial institutions with long-term commitment an incentive to switch to risky asset in order to attain a higher probability of matching their promised yield. The last channel refers to the fact that banks always tend to maintain a constant leverage ratio. The leverage ratio tends to drop with monetary policy easing as risky asset weight falls, and this could lead banks to switch towards risky assets.

Empirically, one stream of the literature focuses on providing evidence and testing the theoretical models. A main identification obstacle these empirical studies face is the difficulty of distinguishing the impact of changes in monetary policy on the loan supply from the impact on loan demand since both will be affected. The other stream employs econometric models to measure the effects of monetary policy shocks on real economy variables. For example, structural vector autoregressive models (SVAR) with a few plausible identification restrictions could provide impulse response functions that describe the impact of monetary policy shocks on specific variables. Most SVAR models include interest rate and real macroeconomic variables only, which may be sufficient to measure the impact of monetary policy shocks, but provide little information on the monetary transmission mechanism.

While there is a huge literature on the effects of monetary policy shocks, very few attempts have been made to measure monetary transmission mechanism itself. One strategy may be to consider the weighted measures of the several individual channels. This could be difficult to implement empirically, though, since different channels arise from different economic models and assumptions, which makes it hard to determine the weight for each measure in aggregate. Another strategy could be to include in one model intermediate variables through which the mechanism is transmitted. This is also challenging since the monetary transmission mechanism has many channels, and there is an array of intermediate variables to be included at different frequencies in the model. However, this can be accomplished with innovating empirical models, as implemented in this paper. We extend the factor-augmented vector autoregressive regression (FAVAR) to a mixed-frequency version to construct a high-frequency coincident index of monetary transmission mechanism in U.S.

We divide the monetary transmission mechanism in three stages according to the timing and order of the effect. The first stage has the fast-moving variables such as asset return measured with high frequency data. The second stage has medium-moving intermediate variables that measure the credit market changes in medium-run frequency. The last stage is the slow-moving real macro variables in low frequency. We propose a baseline model and an alternative model that include many variables and yet reduce the number of parameters to be estimated. The mixed-frequency FAVAR model is estimated with a two-stage maximum likelihood estimation process and yields as output a coincident index that measures the monetary transmission mechanism in U.S.

There are three papers that are closely related to this paper. One is Bernanke, Boivin and Eliasz (2005), who introduce the Factor-Augmented Vector Autoregressive Regression (FAVAR) model. The main advantage of the FAVAR model is that it does not require restrictions on the number of informational variables as the traditional VAR, and still maintains the general framework of VAR analysis. Including large number of informational variables in the model minimizes the mismeasurement problem. Additionally, it makes it closer to the situation faced by central bank or policy makers. Bernanke, Boivin and Eliasz (2005) apply the FAVAR model to 120 monthly U.S. macroeconomic and financial series. The effect of monetary policy shocks is measured by impulse response functions of these variables. A second closely related paper is Mariano and Murasawa (2003), who extent Stock and Watson monthly coincident index by including a variable with at the quarterly frequency, real GDP. They proposed a mixed-frequency one-factor model by filling the missing observations in quarterly data with random draws from standard normal distribution with zero mean. The resulting coincident index is an estimated latent monthly real GDP. Mariano and Murasawa (2010) introduced a mixed-frequency VAR model and a mixed-frequency dynamic K-factor model to estimate a new coincident index of monthly real GDP. While maintaining the same mixed frequency method as in their 2003 paper, they select the number of lags in the VAR model and the number of factors for the dynamic factor model according to model selection criteria, and the resulting coincident indices differ substantially from their previous version.

This paper has three main contributions. First, as most literature on mixed-frequency data have focused on data with two frequencies, we propose a mixed-frequency version of FAVAR model that combines three different frequencies in the same model. Second, the estimation of the proposed model is very time-consuming even with limited number of variables and sample period. Therefore, we developed an alternative approach to largely reduce the number of parameters and simplify the estimation of the original version of MF-FAVAR model. Finally,, we construct a high-frequency coincident index from the model, which measures monetary transmission mechanism in U.S. and provides leading signal for recessions.

The mixed-frequency FAVAR model proposed in this paper is a combination of the original FAVAR model and the mixed-frequency factor model. The proposed model not only allows for a large number of indicators as in the standard FAVAR model, it is also compatible with data from several different frequencies.

The model estimation is implemented using a similar two-step procedure as in standard FAVAR. For the baseline model, in the first step stage factors of different frequencies are estimated individually using the mixed-frequency factor model. The second step uses the estimated factors from step one on standard recursive VAR. However, the fact that the baseline model has too many parameters makes the estimation very time-consuming. We, therefore, propose an alternative method, which replaces some high-frequency data with skip-sampled lower-frequency data in the first step. The second step is adjusted accordingly to be the mixed-frequency VAR model. The resulting coincident index is the estimated latent high-frequency common factor of federal fund rate and real macro variables.

The proposed coincident index of U.S. monetary transmission mechanism measures the effectiveness of the impact of monetary policy on the economy. The dynamics of the index depict the evolution of the U.S. monetary transmission mechanism over the last two decades. There are two major peaks, in 2000 and 2007, indicating the large impact of monetary transmission mechanism driven by rapid expansion of credit market as well as financial innovations. The index also exhibits a clear pattern, in which it reaches local peaks right before the recessions, and it declines during the recessions. This implies that the effectiveness of monetary transmission mechanism could be lessen during recessions.

As far as we know, this is the first paper quantifying the monetary transmission mechanism, thus there are no other comparable indices available. We, thereby, use for comparison, a simple time-varying parameter model to estimate the coefficient of the first difference of federal fund rate in response to the growth rate of real GDP. The result is consistent with the proposed coincident index.

The rest of the paper is structured as follows. Section two presents the proposed mixed-frequency version of factor-augmented vector autoregressive regression model, the alternative model and their corresponding two-stage ML estimation processes. Section three applies the model to U.S. macroeconomic and financial data to construct the coincident index of monetary transmission mechanism, and discuss the empirical results. Section four concludes.

II. The model

A. The Baseline Model

Consider Y_t to be a $M \times 1$ vector of observable economic variables of interest that is driving the economy. In our application, it has federal fund rate in weekly frequency only. After a policy change, due to the nature of the existing economic structure, the impact will go through the variables in a certain order. In the context of monetary policy change, we consider two possible scenarios to track the shockwaves. The first scenario simply follows the classic interest rate channel and bank-lending channel of monetary transmission mechanism in the literature. An increase in interest rate leads to a drop in the amount of credit available to firms and consumers (loan supply), leading to a decrease in investment by firms and consumption by consumers. In the second scenario, we consider balance sheet channel and risk-taking channel in a expectation perspective, as interest rate rises, the amount of credit available to firms and consumers are expected to drop, causing a drop in firms' profitability which is shown in the balance sheet. The asset price and value in financial markets will drop resulting firms and consumers adjust the investment and consumption accordingly. The main difference between the scenarios described above, is the timing (or spreading speed) of the real effect of one monetary policy change. This is not a problem in the standard VAR or FAVAR model since the variables are of the same frequency and the time length for one period is implicitly determined by the frequency of the data. The common assumption in the literature that the variables are not contemporaneously affected by monetary policy shock also implies that the spreading speed is the same for all variables, which may not be a plausible assumption when the frequency of the data is too low.

The solution we propose in this paper is that we measure different variables in different frequency. More specifically, in the context of monetary transmission mechanism, the transmission mechanism is divided into three stages: stage 1 of fast-moving variables such as asset returns are measured in high frequency; stage 2 of medium-moving variables in credit market are measured in medium frequency; stage 3 of real macro variables are considered slow-moving variables measured in low frequency. We extend the standard factor-augmented vector autoregressive regression (FAVAR) model to a mixed-frequency version by assuming three unobservable factors $f_{1,t}$, $f_{2,t}$ and $f_{3,t}$ of low, medium and high frequency respectively that summarize the information of different stages in monetary transmission mechanism. Officially, a of three-stage mixed-frequency FAVAR model is given by

$$\begin{bmatrix} f_{1,t} \\ f_{2,t} \\ f_{3,t} \\ y_t \end{bmatrix} = \phi(L) \begin{bmatrix} f_{1,t-1} \\ f_{2,t-1} \\ f_{3,t-1} \\ y_t \end{bmatrix} + \mathbf{v}_t \tag{1}$$

where $\phi(L)$ is a lag polynomial of order d and $v_t\tilde{}NID(0, Q)$. Note that the factors are ordered from low to high frequency and federal fund rate is placed at the bottom as in standard literature.

The unobservable factors are interpreted as the indicators of different stages in monetary transmission mechanism, which are extracted from various related informational economic variables. Let $X_{1,t}$, $X_{2,t}$, $X_{3,t}$ be $N_1 \times T_1$, $N_2 \times T_2$, $N_3 \times T_3$ informational data we observe at low, medium and high frequency respectively with N_i being the number of variables and T_i the number of observations $i = 1, 2, 3$. The time length of one period in the model is set to be consistent with that of the highest frequency data, namely $X_{3,t}$. Therefore, $X_{3,t}$ is observed every period, while $X_{2,t}$ and $X_{1,t}$ is observed every n and m period where $m > n > 1$. In the case of $X_{3,t}$ being weekly data, $X_{2,t}$ being monthly data and $X_{1,t}$ being quarterly data, we can set $m = 12$ and $n = 4$.

Following Mariano and Murasawa (2003), let $X_{1,t}^*$ and $X_{2,t}^*$ be the underlying latent variable in highest frequency such that the observed variable is equal to the geometric average of the last three periods' latent variable. Formally,

$$\begin{aligned}\ln x_{1,t} &= \frac{1}{3}(\ln x_{1,t}^* + \ln x_{1,t-1}^* + \ln x_{1,t-2}^*)\\ \ln x_{2,t} &= \frac{1}{3}(\ln x_{2,t}^* + \ln x_{2,t-1}^* + \ln x_{2,t-2}^*)\end{aligned}$$

Let $y_{1,t} = \Delta_{12} \ln x_{1,t}$, $y_{1,t}^* = \Delta \ln x_{1,t}^*$, $y_{2,t} = \Delta_4 \ln x_{2,t}$, $y_{2,t}^* = \Delta \ln x_{2,t}^*$ and $y_{3,t} = \Delta \ln x_{3,t}$. We have

$$y_{1,t} = \frac{1}{3}y_{1,t}^* + \frac{2}{3}y_{1,t-1}^* + y_{1,t-2}^* + ... + y_{1,t-11}^* + \frac{2}{3}y_{1,t-12}^* + \frac{1}{3}y_{2,t-13}^* \tag{2}$$

$$y_{2,t} = \frac{1}{3}y_{2,t}^* + \frac{2}{3}y_{2,t-1}^* + y_{2,t-2}^* + y_{2,t-3}^* + \frac{2}{3}y_{2,t-4}^* + \frac{1}{3}y_{2,t-5}^* \tag{3}$$

Let

$$\mathbf{y}_{1,t} = \begin{pmatrix} y_{1,t} \\ y_t \end{pmatrix}$$

$$\mathbf{y}^*_{1,t} = \begin{pmatrix} y^*_{1,t} \\ y_t \end{pmatrix}$$

Define $\mu_i = E(y_{i,t}), i = 1, 2,\ \mu_y = E(y_t)$ and

$$\boldsymbol{\mu}_i = \begin{pmatrix} \mu_i \\ \mu_y \end{pmatrix}$$

$$\boldsymbol{\mu}^*_i = \begin{pmatrix} \mu^*_i \\ \mu_y \end{pmatrix}$$

Then relationship between $\mathbf{y}_{1,t}$ and $\mathbf{y}^*_{1,t}$ could be written as

$$\mathbf{y}_{1,t} - \boldsymbol{\mu}_1 = \mathbf{J}_1(L)(\mathbf{y}^*_{1,t} - \boldsymbol{\mu}^*_1) \tag{4}$$

where

$$\begin{aligned}\mathbf{J}_1(L) &= \begin{pmatrix} \frac{1}{3}\mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & 1 \end{pmatrix} + \begin{pmatrix} \frac{2}{3}\mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L + \begin{pmatrix} \mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L^2 + ... \\ &+ \begin{pmatrix} \mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L^{11} \begin{pmatrix} \frac{2}{3}\mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L^{12} + \begin{pmatrix} \frac{1}{3}\mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L^{13}\end{aligned}$$

Similarly, for $\mathbf{y}_{2,t}$ and $\mathbf{y}^*_{2,t}$

$$\mathbf{y}_{2,t} - \boldsymbol{\mu}_2 = \mathbf{J}_2(L)(\mathbf{y}^*_{2,t} - \boldsymbol{\mu}^*_2) \tag{5}$$

where

$$\mathbf{J}_2(L) = \begin{pmatrix} \frac{1}{3}\mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & 1 \end{pmatrix} + \begin{pmatrix} \frac{2}{3}\mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L + \begin{pmatrix} \mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L^2 + \\ + \begin{pmatrix} \mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L^3 \begin{pmatrix} \frac{2}{3}\mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L^4 + \begin{pmatrix} \frac{1}{3}\mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L^5$$

For each stage, we hope to extract the common factor between monetary policy and informational variables in the stage, which is interpreted as linkage between monetary policy and economic variables of corresponding stage. For stage 2 and stage 3, the factor is related to informational data using a mixed-frequency dynamic factor model because of frequency difference. In stage 1, we maintain the factor model as in standard FAVAR:

$$\begin{pmatrix} y_{1,t} \\ y_t \end{pmatrix} = \begin{pmatrix} \mu_1 \\ \mu_y \end{pmatrix} + \begin{pmatrix} \beta_{11}(\frac{1}{3}f_{1,t} + \frac{2}{3}f_{1,t-1} + \sum_{j=2}^{11} f_{1,t-j} + \frac{2}{3}f_{1,t-12} + \frac{1}{3}f_{1,t-13}) \\ \beta_{12}f_{1,t} \end{pmatrix} \\ + \begin{pmatrix} \frac{1}{3}e_{1,t} + \frac{2}{3}e_{1,t-1} + \sum_{j=2}^{11} e_{1,t-j} + \frac{2}{3}e_{1,t-12} + \frac{1}{3}e_{1,t-13} \\ e_t \end{pmatrix} \tag{6}$$

$$\begin{pmatrix} y_{2,t} \\ y_t \end{pmatrix} = \begin{pmatrix} \mu_2 \\ \mu_y \end{pmatrix} + \begin{pmatrix} \beta_{21}(\frac{1}{3}f_{2,t} + \frac{2}{3}f_{2,t-1} + f_{2,t-2} + f_{2,t-3} + \frac{2}{3}f_{2,t-4} + \frac{1}{3}f_{2,t-5}) \\ \beta_{22}f_{2,t} \end{pmatrix} \\ + \begin{pmatrix} \frac{1}{3}e_{2,t} + \frac{2}{3}e_{2,t-1} + e_{2,t-2} + e_{2,t-3} + \frac{2}{3}e_{2,t-4} + \frac{1}{3}e_{2,t-5}) \\ e_t \end{pmatrix} \tag{7}$$

$$y_{3,t} = \Lambda_3 f_{3,t} + \Lambda_i^y y_t + e_{3,t} \tag{8}$$

where β_{ij} are corresponding factor loading vectors, $\boldsymbol{\beta}_i = (\beta'_{i1}, \beta'_{i2})', i = 1, 2$; Λ_3 is $N_3 \times K$ factor loading matrix; $e_{3,t}$ is $N_3 \times 1$ error term vectors.

B. Estimation

The model could be estimated using a similar two-step procedure as in standard FAVAR literature. The first step is to estimate factors $\hat{f}_i, i = 1, 2, 3$ individually. To estimate (6), first we need to assume AR process for $f_{1,t}$ and $e_{1,t}$:

$$
\begin{aligned}
&(9) \qquad & \phi_1^f(L) f_{1,t} &= v_{11,t} \\
&(10) \qquad & \Phi_1^e(L) e_{1,t} &= v_{12,t}
\end{aligned}
$$

$$\begin{pmatrix} v_{1,t} \\ v_{2,t} \end{pmatrix} \tilde{\ } NID(0, \begin{pmatrix} \sigma_1^2 & 0 \\ 0 & \Sigma_{22} \end{pmatrix})$$

where $\phi_1^f(L)$ is a lag operation polynomial of p_1th-order and $\Phi_1^e(L)$ is a lag operation polynomial of q_1th order. The variance-covariance matrix is assumed to be diagonal with the first element equals 1, which is standard identification strategy in factor model literature.

Define the state vector to be

$$\mathbf{s}_{1,t} = \begin{pmatrix} f_{1,t} \\ \vdots \\ f_{1,t-13} \\ u_{1,t} \\ \vdots \\ u_{1,t-13} \end{pmatrix}$$

where $u_{1,t} = (e'_{1,t}, e'_t)'$. The state-space representation when $p_1, q_1 \leq 14$ could be written as

$$
\begin{aligned}
&(11) \qquad & \mathbf{s}_{1,t} &= \mathbf{F}_1 \mathbf{s}_{1,t-1} + \mathbf{G}_1 \mathbf{z}_{1,t} \\
&(12) \qquad & \mathbf{y}_{1,t} &= \boldsymbol{\mu}_1 + \mathbf{H}_1 \mathbf{s}_t
\end{aligned}
$$

$$\{\mathbf{z}_{1,t}\} \tilde{\ } IN(\mathbf{0}, \mathbf{I}_{N_1+1})$$

where

$$
\begin{aligned}
\mathbf{F}_1 &= \begin{bmatrix} \phi_1^f(1)\cdots\phi_1^f(p_1) & \mathbf{o}'_{14-p_1} & \mathbf{O}_{14\times 14(N_1+1)} & \\ \mathbf{I}_{13} & \mathbf{o}_{13} & & \\ & & \Phi_1^e(1)\cdots\Phi_1^e(q_1) & \mathbf{O}_{(N_1+1)\times(14-q_1)(N_1+1)} \\ \mathbf{O}_{14(N_1+1)\times 14} & & \mathbf{I}_{13(N_1+1)} & \mathbf{O}_{13(N_1+1)\times(N_1+1)} \end{bmatrix} \\
\mathbf{G}_1 &= \begin{bmatrix} \sigma_1 & \mathbf{o}_{(N_1+1)} \\ \mathbf{o}_{13} & \mathbf{O}_{13\times(N_1+1)} \\ \mathbf{o}_{(N_1+1)} & \mathbf{\Sigma}_{22}^{1/2} \\ \mathbf{o}_{13(N_1+1)} & \mathbf{O}_{13(N_1+1)\times(N_1+1)} \end{bmatrix} \\
\mathbf{H}_1 &= \begin{bmatrix} \mathbf{J}_1(0)\boldsymbol{\beta}_1 & \cdots & \mathbf{J}_1(13)\boldsymbol{\beta}_1 & \mathbf{J}_1(0) & \cdots & \mathbf{J}_1(13) \end{bmatrix}
\end{aligned}
$$

Similarly, we can write the state-space representation of (7) when $p_2, q_2 \leq 6$ as

$$
\mathbf{s}_{2,t} = \mathbf{F}_2\mathbf{s}_{2,t-1} + \mathbf{G}_2\mathbf{z}_{1,t} \tag{13}
$$

$$
\mathbf{y}_{2,t} = \boldsymbol{\mu}_2 + \mathbf{H}_2\mathbf{s}_t \tag{14}
$$

$$
\{\mathbf{z}_{2,t}\}\tilde{\ } IN(\mathbf{0}, \mathbf{I}_{N_2+1})
$$

where

$$
\mathbf{s}_{2,t} = \begin{pmatrix} f_{2,t} \\ \vdots \\ f_{2,t-5} \\ u_{2,t} \\ \vdots \\ u_{2,t-5} \end{pmatrix}
$$

$$
\mathbf{F}_2 = \begin{bmatrix} \phi_2^f(1)\cdots\phi_2^f(p_2) & \mathbf{o}'_{6-p_2} & \mathbf{O}_{6\times 6(N_1+1)} & \\ \mathbf{I}_5 & \mathbf{o}_5 & & \\ & & \Phi_2^e(1)\cdots\Phi_2^e(q_2) & \mathbf{O}_{(N_2+1)\times(6-q_2)(N_2+1)} \\ \mathbf{O}_{6(N_1+1)\times 6} & & I_{5(N_2+1)} & \mathbf{O}_{5(N_2+1)\times(N_2+1)} \end{bmatrix}
$$

$$
\mathbf{G}_2 = \begin{bmatrix} \sigma_2 & \mathbf{o}_{(N_2+1)} \\ \mathbf{o}_{13} & \mathbf{O}_{5\times(N_2+1)} \\ \mathbf{o}_{(N_2+1)} & \mathbf{\Sigma}_{22}^{1/2} \\ \mathbf{o}_{5(N_2+1)} & \mathbf{O}_{5(N_2+1)\times(N_2+1)} \end{bmatrix}
$$

$$
\mathbf{H}_2 = \begin{bmatrix} \mathbf{J}_2(0)\boldsymbol{\beta}_2 & \cdots & \mathbf{J}_2(5)\boldsymbol{\beta}_2 & \mathbf{J}_2(0) & \cdots & \mathbf{J}_2(5) \end{bmatrix}
$$

The above two models could be estimated using the standard method to get the estimated factors $\hat{f}_{1,t}$ and $\hat{f}_{2,t}$. For (8), $\hat{f}_{3,t}$ could be estimated using principal component method as in standard FAVAR model.

Note that the estimates of the factors are all of the highest frequency, the second step could just follow the standard FAVAR model to estimate (1) under the recursive VAR environment.

C. The Alternative Model

One disadvantage of the baseline model is that the time of estimation is too long as we can observe the number of parameters in (6) is too large. In our application, we used an alternative model that could greatly reduce the number of lags and coefficients to simply the estimation.

The alternative model replace the high-frequency series y_t in (6) with medium-frequency series y_t^m which is skip-sampled from y_t. Accordingly, we have to make following adjustments.

Let $y_{1,t}^m = \Delta_3 \ln x_{1,t}$, we have

$$
y_{1,t}^m = \frac{1}{3}y_{1,t}^* + \frac{2}{3}y_{1,t-1}^* + y_{1,t-2}^* + \frac{2}{3}y_{1,t-3}^* + \frac{1}{3}y_{1,t-4}^* \tag{15}
$$

Define $\mu_1^m = E(y_{1,t}^m)$, $\mu_y^m = E(y_t^m)$ and

$$\boldsymbol{\mu}_1^m = \begin{pmatrix} \mu_1^m \\ \mu_y \end{pmatrix}$$

Thus the relationship between $y_{1,t}^m$ and $y_{1,t}^*$ is given by

$$\mathbf{y}_{1,t}^m - \boldsymbol{\mu}_1 = \mathbf{J}_1(L)(\mathbf{y}_{1,t}^* - \boldsymbol{\mu}_1^*)$$

where

$$\begin{aligned}
\mathbf{y}_{1,t}^m &= \begin{pmatrix} y_{1,t}^m \\ y_t \end{pmatrix} \\
\mathbf{J}_1^m(L) &= \begin{bmatrix} \frac{1}{3}\mathbf{I}_1 & \mathbf{O} \\ \mathbf{O} & \mathbf{I}_N \end{bmatrix} + \begin{bmatrix} \frac{2}{3}\mathbf{I}_1 & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{bmatrix} L + \begin{bmatrix} \mathbf{I}_1 & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{bmatrix} L^2 \\
&\quad + \begin{bmatrix} \frac{2}{3}\mathbf{I}_1 & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{bmatrix} L^3 + \begin{bmatrix} \frac{1}{3}\mathbf{I}_1 & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{bmatrix} L^4
\end{aligned}$$

The alternative model is given by

$$\begin{aligned}
\begin{pmatrix} y_{1,t}^m \\ y_t^m \end{pmatrix} &= \begin{pmatrix} \mu_1^m \\ \mu_y^m \end{pmatrix} + \begin{pmatrix} \beta_{11}(\frac{1}{3}f_{1,t} + \frac{2}{3}f_{1,t-1} + f_{1,t-2} + \frac{2}{3}f_{1,t-3} + \frac{1}{3}f_{1,t-4}) \\ \beta_{12}f_{1,t} \end{pmatrix} \\
&\quad + \begin{pmatrix} \frac{1}{3}e_{1,t} + \frac{2}{3}e_{1,t-1} + e_{1,t-2} + \frac{2}{3}e_{1,t-3} + \frac{1}{3}e_{1,t-4} \\ e_t^m \end{pmatrix} \qquad (16)
\end{aligned}$$

The state-space representation when $p_1, q_1 \leq 5$ is given by

$$\mathbf{s}_{1,t}^m = \mathbf{F}_1^m \mathbf{s}_{1,t-1}^m + \mathbf{G}_1^m \mathbf{z}_{1,t} \qquad (17)$$

$$\mathbf{y}_{1,t}^m = \boldsymbol{\mu}_1^m + \mathbf{H}_1^m \mathbf{s}_t^m \qquad (18)$$

$$\{\mathbf{z}_{1,t}\}\tilde{}IN(\mathbf{0},\mathbf{I}_{N_1+1})$$

where

$$\mathbf{s}_{1,t}^m = \begin{pmatrix} f_{1,t} \\ \vdots \\ f_{1,t-4} \\ u_{1,t} \\ \vdots \\ u_{1,t-4} \end{pmatrix}$$

$$\begin{aligned}
\mathbf{F}_1^m &= \begin{bmatrix} \phi_1^f(1)\cdots\phi_1^f(p_1) & \mathbf{o}_{5-p_1}' & \mathbf{O}_{5\times 5(N_1+1)} & \\ \mathbf{I}_4 & \mathbf{o}_{14} & & \\ & & \Phi_1^e(1)\cdots\Phi_1^e(q_1) & \mathbf{O}_{(N_1+1)\times(5-q_1)(N_1+1)} \\ \mathbf{O}_{5(N_1+1)\times 5} & & \mathbf{I}_{4(N_1+1)} & \mathbf{O}_{4(N_1+1)\times(N_1+1)} \end{bmatrix} \\
\mathbf{G}_1^m &= \begin{bmatrix} \sigma_1 & \mathbf{o}_{(N_1+1)} \\ \mathbf{o}_4 & \mathbf{O}_{4\times(N_1+1)} \\ \mathbf{o}_{(N_1+1)} & \mathbf{\Sigma}_{22}^{1/2} \\ \mathbf{o}_{4(N_1+1)} & \mathbf{O}_{4(N_1+1)\times(N_1+1)} \end{bmatrix} \\
\mathbf{H}_1^m &= \begin{bmatrix} \mathbf{J}_1^m(0)\boldsymbol{\beta}_1 & \cdots & \mathbf{J}_1^m(4)\boldsymbol{\beta}_1 & \mathbf{J}_1^m(0) & \cdots & \mathbf{J}_1^m(4) \end{bmatrix}
\end{aligned}$$

Note that in the alternative model, the estimated factor $\hat{f}_{1,t}$ is in medium frequency, which make the standard VAR in second step no longer applicable. Instead, we adopt mixed-frequency VAR in the second step. Recall (1) with the estimated factors plugged in:

$$\begin{bmatrix} \hat{f}_{1,t} \\ \hat{f}_{2,t} \\ \hat{f}_{3,t} \\ y_t \end{bmatrix} = \phi(L) \begin{bmatrix} \hat{f}_{1,t-1} \\ \hat{f}_{2,t-1} \\ \hat{f}_{3,t-1} \\ y_t \end{bmatrix} + \mathbf{v}_t \tag{19}$$

Let $y_{1,t}^f = \Delta_4 \ln \hat{f}_{1,t}$ and $y_t^{f*} = \Delta \ln \hat{f}_{1,t}^*$, where $\hat{f}_{1,t}^*$ is the latent variable of $\hat{f}_{t,1}$ and $y_{2,t}^f = \Delta \ln \begin{pmatrix} \hat{f}_{2,t} \\ \hat{f}_{3,t} \\ y_t \end{pmatrix}$. Then we have

$$y_{1,t}^f = \frac{1}{3} y_{2,t}^{f*} + \frac{2}{3} y_{2,t-1}^{f*} + y_{2,t-2}^{f*} + y_{2,t-3}^{f*} + \frac{2}{3} y_{2,t-4}^{f*} + \frac{1}{3} y_{2,t-5}^{f*} \tag{20}$$

Let

$$\begin{aligned} \mathbf{y}_t &= \begin{pmatrix} y_{1,t}^f \\ y_{2,t}^f \end{pmatrix} \\ \mathbf{y}_t^* &= \begin{pmatrix} y_{1,t}^{f*} \\ y_{2,t}^f \end{pmatrix} \end{aligned}$$

Define $\boldsymbol{\mu} = E(\mathbf{y}_t)$, $\boldsymbol{\mu}^* = E(\mathbf{y}_t^*)$the relationship between $\mathbf{y}_t$ and $\mathbf{y}_t^*$ is given by

$$\mathbf{y}_t - \boldsymbol{\mu} = \mathbf{J}(L)(\mathbf{y}_t^* - \boldsymbol{\mu}^*) \tag{21}$$

where

$$\begin{aligned} \mathbf{J}(L) &= \begin{pmatrix} \frac{1}{3}\mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & 1 \end{pmatrix} + \begin{pmatrix} \frac{2}{3}\mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L + \begin{pmatrix} \mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L^2 + \\ & \quad + \begin{pmatrix} \mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L^3 + \begin{pmatrix} \frac{2}{3}\mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L^4 + \begin{pmatrix} \frac{1}{3}\mathbf{I}_{N_1} & \mathbf{O} \\ \mathbf{O} & \mathbf{O} \end{pmatrix} L^5 \end{aligned}$$

Assume $\mathbf{y}_t^*$ follows Gaussian VAR(p)

$$\boldsymbol{\phi}(L)(\mathbf{y}_t^* - \boldsymbol{\mu}^*) = \mathbf{w}_t, \mathbf{w}_t \tilde{\ } IN(\mathbf{0}, \boldsymbol{\Sigma}) \tag{22}$$

Let the state variable be

$$\mathbf{s}_t = \begin{pmatrix} \mathbf{y}_t^* - \boldsymbol{\mu}^* \\ \vdots \\ \mathbf{y}_{t-5}^* - \boldsymbol{\mu}^* \end{pmatrix}$$

The state-space representation when $p \leq 6$ is given by

$$\mathbf{s}_{t+1} = \mathbf{A}\mathbf{s}_t + \mathbf{B}\mathbf{z}_t \tag{23}$$

$$\mathbf{y}_t = \boldsymbol{\mu} + \mathbf{C}\mathbf{s}_t \tag{24}$$

$$\{\mathbf{z}_t\}\tilde{\ } IN(\mathbf{0}, \mathbf{I}_{K+3})$$

where

$$\begin{aligned} \mathbf{A} &= \begin{bmatrix} \boldsymbol{\phi}_1 & \cdots & \boldsymbol{\phi}_p & \mathbf{O}_{(K+3)\times(6-p)(K+3)} \\ & \mathbf{I}_{5(K+3)} & & \mathbf{O}_{5(K+3)\times(K+2)} \end{bmatrix} \\ \mathbf{B} &= \begin{bmatrix} \boldsymbol{\Sigma}^{1/2} \\ \mathbf{O}_{5(K+3)\times(K+3)} \end{bmatrix} \\ \mathbf{C} &= \begin{bmatrix} \mathbf{J}(0) & \cdots & \mathbf{J}(5) \end{bmatrix} \end{aligned}$$

For all the mixed-frequency models above, the lower frequency series are not always observable. Follow Mariano and Murasawa (2003), we replace the missing observations with random variable $\epsilon_t \tilde{\ } N(0,1)$ which has a realization of 0 and adjust the rest of the measurement equation accordingly. For example, the measurement equation (24) can be written as

$$\begin{pmatrix} y_{1,t}^f \\ y_{2,t}^f \end{pmatrix} = \begin{pmatrix} \boldsymbol{\mu}(1) \\ \boldsymbol{\mu}(2) \end{pmatrix} + \begin{pmatrix} \mathbf{C}(1) \\ \mathbf{C}(2) \end{pmatrix} \mathbf{s}_t \tag{25}$$

With the missing values replaced, the measurement equation becomes

$$\mathbf{y}_t^+ = \boldsymbol{\mu}_t + \mathbf{C}_t \mathbf{s}_t + \mathbf{D}_t \epsilon_t \tag{26}$$

where

$$\begin{aligned} \mathbf{y}_t^+ &= \begin{pmatrix} y_{1,t}^{f+} \\ y_{2,t}^{f} \end{pmatrix}, \boldsymbol{\mu}_t = \begin{pmatrix} \boldsymbol{\mu}_t(1) \\ \boldsymbol{\mu}_t(2) \end{pmatrix} \\ \mathbf{C}_t &= \begin{pmatrix} \mathbf{C}_t(1) \\ \mathbf{C}_t(2) \end{pmatrix}, \mathbf{D}_t = \begin{pmatrix} \mathbf{D}_t(1) \\ \mathbf{O} \end{pmatrix} \end{aligned}$$

$$\begin{aligned} y_{1,t}^{f+} &= \left\{ \begin{array}{c} y_{1,t}^{f} \text{ if } \mathbf{y}_t \text{ observed} \\ \epsilon_t \text{ if } \mathbf{y}_t \text{ not observed} \end{array} \right., \boldsymbol{\mu}_t(1) = \left\{ \begin{array}{c} \boldsymbol{\mu}(\mathbf{1}) \text{ if } \mathbf{y}_t \text{ observed} \\ \mathbf{0} \text{ if } \mathbf{y}_t \text{ not observed} \end{array} \right. \\ \mathbf{C}_t(1) &= \left\{ \begin{array}{c} \mathbf{C}(\mathbf{1}) \text{ if observed} \\ \mathbf{O} \text{ if not observed} \end{array} \right., \mathbf{D}_t(1) = \left\{ \begin{array}{c} \mathbf{D}(1) \text{ if observed} \\ 1 \text{ if not observed} \end{array} \right. \end{aligned}$$

The state-space representation with missing values replaced is given by

$$\mathbf{s}_{t+1} = \mathbf{A}\mathbf{s}_t + \mathbf{B}\mathbf{z}_t \tag{27}$$

$$\mathbf{y}_t^+ = \boldsymbol{\mu}_t + \mathbf{C}_t \mathbf{s}_t + \mathbf{D}_t \epsilon_t \tag{28}$$

$$\left\{ \begin{pmatrix} \mathbf{z}_t \\ \epsilon_t \end{pmatrix} \right\} \tilde{\ } IN(\mathbf{0}, \mathbf{I}_{K+4})$$

Now that $\{\mathbf{y}_t^+\}$ has no missing values, the Kalman filter can apply directly.

III. Application

A. Data

We apply the mixed-frequency FAVAR model to US economy data to construct a measurement of monetary transmission mechanism. The series we use are of three frequencies sampled from July 1987 to December 2015. Quarterly indicators are "slow-moving" variables that measure the real economy activities. Monthly indicators are chosen to be variables that reflects the loan and credit change in financial intermediates. Weekly indicators are mostly "fast-moving" return rates that reflects the financial market movement. Note that for each month we may have either four or five weekly observations, we made the following adjustment for months of the latter case. Let $\{x_t, ...x_{t+4}\}$ be the five weekly observations in a month. The adjusted observations are given by

$$\{\frac{1}{2}(x_t + x_{t+1}), \frac{1}{2}(x_{t+1} + x_{t+2}), \frac{1}{2}(x_{t+2} + x_{t+3}), \frac{1}{2}(x_{t+3} + x_{t+4})\}$$

Since weekly indicators are return rates in level, the average of adjacent observations could be considered as pseudo observation over the this time period. This will guarantee us four weekly observations every month.

All the series are selected based on three criterion: whether the movement speed of variable matches its frequency of being observed; whether the variable fits in the potential process of monetary transmission mechanism; whether the variable is available within the sample period. Since the estimation is very time-consuming, we carefully restrict our number of variables and time window within an acceptable range. Table 1 summarizes the detailed descriptions of the series. "SA" stands for "seasonally adjusted", "NSA" stands for "not seasonally adjusted" and "AR" stands for "annual rate". All data are directly downloaded from FRED, except Divisia M4 is provided by Center for Financial Stability.

Table 2 summarizes the descriptive statistics of the standardize indicators. The transformation codes are: 1 – no transformation; 2 – first difference; 5 – first difference of logarithm.

Since some of the series experienced structural break for regulation reasons, we adopted 1% winsorization to maintain stationarity. As mentioned above, we use the alternative model in our application. The monthly federal fund rate are skip-sampled from original weekly series.

B. *Estimated Results*

The number of lags for AR process are determined using information criterion AIC and SBIC same in Mariano and Murasawa (2003):

$$AIC = -\frac{1}{T}\{\ln L(\hat{\theta}) - [(N-1) + p + 1 + N(q+1)]\} \tag{29}$$

$$SBIA = -\frac{1}{T}\{\ln L(\hat{\theta}) - \frac{\ln T}{2}[(N-1) + p + 1 + N(q+1)]\} \tag{30}$$

The selected model are $(p_1, q_1) = (2, 1)$, $(p_2, q_2) = (1, 1)$ and $p = 1$. The number of factors are in the principal component $K = 2$ chosen using cross-validation.

We followed the standard literature to have the series demeaned so all the constant terms in the models are deleted. Using Ox 7.10 and code modified from Mariano and Murasawa (2003, 2010), the approximate ML estimator could be estimated using quasi-Newton method. Table 3 and 4 summarized the estimated result of the mixed-frequency factor model in the first stage.

The estimated factors from quarterly indicators and monthly indicators are shown in Figure 1 and 2 respectively. We can observe that factor estimated from quarterly indicators is more active during the recession while factor estimated from monthly indicator is more active prior to the recession. This is consistent with our assumption that credit market variables in stage 2 react faster to monetary policy change than real macro variables in stage 3. We can construct the coincident index at this stage by taking the exponential of partial sum for each series, shown in Figure 3 and 4. With the shaded area being NBER recession dates, we can see the quarterly index has significant leading signal on the recessions in 2001 and 2007. Monthly index, on the other hand has a spike during the 2007 recession. Both indices failed to capture the 1990 recession. Figure 5 and 6 show the first two principal components of weekly indicators. Both principal components have greater deviation from average during the recession periods.

The having all the estimated factors plugged in, the monetary linkage factor is estimated in the second stage, which is the weekly latent factor estimated from quarterly indicators, shown in figure 7. Again by taking the exponential of partial sum, the constructed coincident index is shown in figure 8. The coincident index is meant to capture the common factor component of real economy variables and federal fund rate in weekly frequency. The index exhibits clear leading signal for the latest two recessions in 2001 and 2007. If we room in for the period of 1987Q3 to 1993Q4 as shown in figure 9, the index captures the recession in 1990 as well. Note that at the end of 2007 recession, the index declines to almost zero by the fact that the effective federal fund rate was approaching the Zero Lower Bound.

To our best knowledge, there is no other coincident index that we know of that we can compare our coincident index with. Therefore, we run a simple exercise following time-varing-parameter model by Kim and Nelson (1989). Consider the following model

$$d\log(GDP_t) = \beta_{0,t} + \beta_{1,t} dffr + \beta_{2,t} d\log(GDP_{t-1}) + e_t \tag{31}$$

$$\beta_{i,t} = \beta_{i,t-1} + v_{i,t}, i = 0, 1, 2 \tag{32}$$

$$\left\{ \begin{pmatrix} e_t \\ v_t \end{pmatrix} \right\} \tilde{\ } IN(\mathbf{0}, \mathbf{\Sigma})$$

where $d\log(GDP_t)$ denotes the growth rate of real GDP and $dffr$ is the first difference of effective federal fund rate. All the data are of quarterly frequency. The estimated time-varying parameter of our interest $\beta_{1,t}$ is shown in figure 10. The coefficient of federal fund rate appear to deviate more from period average during the recessions. Although this model is simple and far from being complete and correct, it shows some strange behavior of monetary transmission mechanism during the recessions which is consistent with our result to some degree.

C. Policy Implications

There are two implications from our coincident index that we could think of. Firstly, our index supports the view that the monetary transmission mechanism has been changing over time. Over the last two decades, the way in which financial market operates, monetary policy implements and information being processed has experienced significant revolutions. The two major peaks in our index around 1999 and 2007 could be explained by the rapid expansion of financial markets as the fluctuations before 1995 are too small to be comparable. The index stays low after 2008, implying that some major traditional channels of monetary transmission mechanism have been shutting down when the effective federal fund rate stays around zero lower-bound. Secondly, the clear pattern that the index reaches local peaks before the recessions and declines during the recessions shows that during the recession the monetary transmission mechanism may not function well as they do in normal times. Various reasons could provide intuition for that: the spread of panic sentiment; overconservative behavior of financial intermediates for example.

In conclusion, the coincident index we construct measures the linkage between federal fund rate and real economy variables in weekly frequency. The most significant feature is that our coincident index provides some leading signal for the recessions in our sample period. Such index could be considered as a measure of monetary transmission mechanism for policy makers.

IV. Conclusion

This paper studies the monetary transmission mechanism in the U.S. It proposes a mixed-frequency version of the factor-augmented vector autoregressive regression (FAVAR) model, which is used to construct a coincident index to measure the monetary transmission mechanism. The model divides the transmission of changes in monetary policy to the economy into three stages according to the timing and order of the impact. Indicators of each stage are measured and identified using different data frequencies: fast-moving variables (stage 1, asset returns at the weekly frequency), intermediate moving variables (stage 2, credit market data at the monthly frequency), and slow-moving variables (stage 3, macroeconomic variables at the quarterly frequency). The resulting coincident index exhibits leading signal for all recessions in the sample period and provides implications on the dynamics of the monetary transmission mechanism. The proposed coincident index also indicates that monetary transmission mechanism is changing over time.

REFERENCES

Baffigi, Alberto, Roberto Golinelli, and Giuseppe Parigi. "Bridge models to forecast the euro area GDP." International Journal of forecasting 20.3 (2004): 447-460.

Bai, Jennie, Eric Ghysels, and Jonathan H. Wright. "State space models and MIDAS regressions." Econometric Reviews 32.7 (2013): 779-813.

Bai, Jushan, and Serena Ng. "Determining the number of factors in approximate factor models." Econometrica 70.1 (2002): 191-221.

Bai, Jushan, and Serena Ng. "Confidence intervals for diffusion index forecasts and inference for factor-Augmented regressions." Econometrica 74.4 (2006): 1133-1150.

Bai, Jushan, and Serena Ng. "Determining the number of primitive shocks in factor models." Journal of Business & Economic Statistics 25.1 (2007): 52-60.

Barnett, William A., Marcelle Chauvet, and Danilo Leiva-Leon. Real-time nowcasting of nominal GDP under structural breaks. No. 2014-39. Bank of Canada Working Paper, 2014.

Beck, Thorsten, Andrea Colciago, and Damjan Pfajfar. "The role of financial intermediaries in monetary policy transmission." Journal of Economic Dynamics and Control 43 (2014): 1-11.

Bernanke, B., and Gertler, M., 1989. Agency Costs, Net Worth and Business Fluctuations. American Economic Review 79, 14-31.

Bernanke, Ben S., Jean Boivin, and Piotr Eliasz. Measuring the effects of monetary policy: a factor-augmented vector autoregressive (FAVAR) approach. No. w10220. National Bureau of Economic Research, 2004.

Boivin, Jean, Michael T. Kiley, and Frederic S. Mishkin. How has the monetary transmission mechanism evolved over time?. No. w15879. National Bureau of Economic Research, 2010.

Bry, Gerhard, and Charlotte Boschan. "Front matter to" Cyclical Analysis of Time Series: Selected Procedures and Computer Programs"." Cyclical Analysis of Time Series: Selected Procedures and Computer Programs. NBER, 1971. 13-2.

Buch, Claudia M., Sandra Eickmeier, and Esteban Prieto. "In search for yield? Survey-based evidence on bank risk taking." Journal of Economic Dynamics and Control 43 (2014): 12-30.

Carpenter, S.B., Demiralp, S., Eisenschmidt, J., 2014. The effectiveness of nonstandard monetary policy in addressing liquidity risk during the financial crisis: The experiences of the Federal Reserve and the European Central Bank. J. Econ. Dyn. Control

Christiano, Lawrence J., and Martin Eichenbaum. Liquidity effects and the monetary transmission mechanism. No. w3974. National Bureau of Economic Research, 1992.

Christiano, Lawrence J., and Martin Eichenbaum. "Liquidity effects, monetary policy, and the business cycle." Journal of Money, Credit and Banking (1995): 1113-1136.

Christiano, Lawrence J., Martin Eichenbaum, and Charles L. Evans. "Monetary policy shocks: What have we learned and to what end?." Handbook of macroeconomics 1 (1999): 65-148.

Christiano, Lawrence, Roberto Motto, and Massimo Rostagno. Two reasons why money and credit may be useful in monetary policy. No. w13502. National Bureau of Economic Research, 2007.

Frale, Cecilia, et al. "EUROMIND: a monthly indicator of the euro area economic conditions." Journal of the Royal Statistical Society: Series A (Statistics in Society) 174.2 (2011): 439-470.

Foroni, Claudia, and Massimiliano Giuseppe Marcellino. "A survey of econometric methods for mixed-frequency data." (2013).

Ghysels, Eric. "Macroeconomics and the reality of mixed frequency data." Journal of Econometrics 193.2 (2016): 294-314.

Ghysels, Eric, Pedro Santa-Clara, and Rossen Valkanov. "The MIDAS touch: Mixed data sampling regression models." Finance (2004).

Harding, Don, and Adrian Pagan. "Synchronization of cycles." Journal of Econometrics 132.1 (2006): 59-79.

He, Zhiguo, and Arvind Krishnamurthy. A macroeconomic framework for quantifying systemic risk. No. w19885. National Bureau of Economic Research, 2014.

Kashyap, A.K., Stein, J.C., 1995. The impact of monetary policy on bank balance sheets. Carnegie-Rochester Conf. Ser. Public Policy 42(1), 151–195.

Killian, Lutz (1996), 'Small - Sample Conference Intervals for Impulse Response Functions', manuscript, University of Pennsylvania.

Kim, Chang-Jin, and Charles R. Nelson. "The time-varying-parameter model for modeling changing conditional variance: The case of the lucas hypothesis." Journal of Business & Economic Statistics 7.4 (1989): 433-440.

Kim, Chang-Jin, and Charles R. Nelson. "Business cycle turning points, a new coincident index, and tests of duration dependence based on a dynamic factor model with regime switching." The Review of Economics and Statistics 80.2 (1998): 188-201.

Kim, Chang-Jin, and Charles R. Nelson. "State-space models with regime switching." (1999).

King, Robert, et al. "Stochastic trends and economic fluctuations." (1987).

King, Robert G. (1991), 'Money and Business Cycles', manuscript, University of Rochester.

Mariano, Roberto S., and Yasutomo Murasawa. "A new coincident index of business cycles based on monthly and quarterly series." Journal of applied Econometrics 18.4 (2003): 427-443.

Mariano, Roberto S., and Yasutomo Murasawa. "A coincident index, common factors, and monthly real GDP." Oxford Bulletin of Economics and Statistics 72.1 (2010): 27-46.

Nicolo G.D., Dell'Ariccia, G., Laeven, L., Valencia, F., 2010. Monetary Policy and Bank Risk-Taking. IMF Staff Position Notes 2010/09, International Monetary Fund.

Schorfheide, Frank, and Dongho Song. "Real-time forecasting with a mixed-frequency VAR." Journal of Business & Economic Statistics 33.3 (2015): 366-380.

Sims, Christopher A. "Macroeconomics and reality." Econometrica: Journal of the Econometric Society (1980): 1-48.

Stock, James H., and Mark W. Watson. "A probability model of the coincident economic indicators." (1988).

Stock, James, and Mark Watson, "New Indexes of Coincident and Leading Economic Indicators", NBER Macroeconomics Annual (4), Cambridge MA: MIT Press, 1989.

Stock, James H., and Mark W. Watson. Diffusion indexes. No. w6702. National Bureau of Economic Research, 1998.

Stock, James H., and Mark W. Watson. "Estimating turning points using large data sets." Journal of Econometrics 178 (2014): 368-381.

Taylor, John B. "The monetary transmission mechanism: an empirical framework." The Journal of Economic Perspectives 9.4 (1995): 11-26.

Tobin, J., 1969. A general equilibrium approach to monetary theory. J. Money Credit Bank. 1 (1), 15–29.

Table 1: US MonetaryTtransmission Mechanism Indicators

Indicator	Description
	Quarterly
outbs	Business Sector: Real Output (2009=100,SA)
outmdgs	Manufacturing Durable Goods Sector: Real Output (2009=100,SA)
outms	Manufacturing Sector: Real Output (2009=100,SA)
outnfb	Nonfarm Business Sector: Real Output (2009=100,SA)
pcec	Personal Consumption Expenditures (SAAR)
pcdg	Personal Consumption Expenditures: Durable Goods (SAAR)
pcend	Personal Consumption Expenditures: Nondurable Goods (SAAR)
pcesv	Personal Consumption Expenditures: Services (BIL 09$, SAAR)
gdpc	Real Gross Domestic Product (BIL 09$, SAAR)
	Monthly
busloans	Commercial and Industrial Loans, All Commercial Banks (BIL$, SA)
consumer	Consumer Loans at All Commercial Banks (BIL$, SA)
iblacbm027sbog	Interbank Loans, All Commercial Banks (BIL$, SA)
invest	Securities in Bank Credit at All Commercial Banks (BIL$, SA)
lcbacbm027sbog	Loans to Commercial Banks , All Commercial Banks (BIL$, SA)
loaninv	Bank Credit at All Commercial Banks (BIL$, SA)
loans	Loans and Leases in Bank Credit, All Commercial Banks (BIL$, SA)
dm4	CFS Divisia M4 (PERCENTAGE GROWTH RATE)
ollacbm027sbog	Other Loans and Leases, All Commercial Banks (BIL$, SA)
olracbm027sbog	Other Loans and Leases: Fed Funds and Reverse RPs with Nonbanks All Commercial Banks (BIL$, SA)
realln	Real Estate Loans, All Commercial Banks (BIL$, SA)
	Weekly
wgs10yr	10-Year Treasury Constant Maturity Rate (PERCENT, NSA)
wgs5yr	5-Year Treasury Constant Maturity Rate (PERCENT, NSA)
wgs1yr	1-Year Treasury Constant Maturity Rate (PERCENT, NSA)
wgs6mo	6-Month Treasury Constant Maturity Rate (PERCENT, NSA)
wgs3mo	3-Month Treasury Constant Maturity Rate (PERCENT, NSA)
waaa	Moody's Seasoned Aaa Corporate Bond Yield (PERCENT, NSA)
wbaa	Moody's Seasoned Baa Corporate Bond Yield (PERCENT, NSA)
ff	Effective Federal Funds Rate (PERCENT, NSA)

Table 2: Descriptive Statistics for Standarized Indicators

Indicator	Transformation Code	Mean	Std. Dev.	Max.	Min.
			Quarterly		
outbs	5	0.006945	0.007965	0.021729	-0.029583
outmdgs	5	0.006356	0.023152	0.048905	-0.121451
outms	5	0.005168	0.018717	0.044756	-0.101291
outnfb	5	0.006943	0.008171	0.022858	-0.031514
pcec	5	0.012201	0.006499	0.025373	-0.026552
pcdg	5	0.009660	0.021472	0.075043	-0.082049
pcend	5	0.010427	0.013082	0.032440	-0.077902
pcesv	5	0.013379	0.005305	0.027369	-0.005832
gdpc	5	0.006228	0.006114	0.018709	-0.021352
			Monthly		
busloans	5	0.003694	0.008671	0.035458	-0.029041
consumer	5	0.004061	0.016825	0.270704	-0.028779
iblacbm027sbog	5	-0.002961	0.049922	0.233067	-0.286793
invest	5	0.005275	0.008864	0.053845	-0.027328
lcbacbm027sbog	5	-0.004149	0.107698	0.327584	-1.204621
loaninv	5	0.004946	0.005151	0.037096	-0.011758
loans	5	0.004835	0.006042	0.046561	-0.016713
dm4	1	0.003669	0.004590	0.022875	-0.017254
ollacbm027sbog	5	0.005503	0.017676	0.065324	-0.075375
olracbm027sbog	5	0.007354	0.054965	0.242955	-0.169333
realln	5	0.005720	0.006732	0.046481	-0.015771
			Weekly		
wgs10yr	2	5.190195	2.079093	10.11000	1.470000
wgs5yr	2	4.638075	2.369535	9.730000	0.590000
wgs1yr	2	3.675740	2.643454	9.780000	0.090000
wgs6mo	2	3.530155	2.631128	9.620000	0.030000
wgs3mo	2	3.380424	2.585795	9.370000	0.000000
waaa	2	6.544966	1.754359	10.73000	3.260000
wbaa	2	7.513075	1.727848	11.78000	4.360000
ff	1	3.580639	2.737047	9.950000	0.050000

Table 3: Estimation Result of Quarterly Indicators

Indicators	β_1	$\phi_1^f(1)$	$\phi_1^f(2)$	σ_1^2	Φ_1^e	Σ_{22}
$\Delta \ln pcdg$	0.29229				-0.83038	1.117
$\Delta \ln pcend$	0.54445				-0.75218	0.70763
$\Delta \ln pcesv$	0.31338				-0.59187	0.81089
$\Delta \lg ndpc$	0.88695				-0.54397	0.011948
$\Delta \ln outbs$	0.87986	-0.53364	0.23524	1	-0.60101	0*
$\Delta \ln outms$	0.28227				0.7742	0.040229
$\Delta \ln outnfb$	0.87501				-0.74225	0.016328
$\Delta \ln pcec$	0.59798				-0.72114	0.67104
$\Delta \ln outmdgs$	0.314				0.65882	0.061898
$\Delta \ln ff^m$	0.0013241				0.99704	0.010551

Table 4: Estimation Result of Monthly Indicators

Indicators	β_2	ϕ_2^f	σ_1^2	Φ_2^e	Σ_{22}
$\Delta \ln busloans$	0.41631			0.80942	0.018899
$\Delta \ln cons$	0.48247			0.58234	0.061351
$\Delta \ln iblac$	0.14838			-0.64904	0.79852
$\Delta \ln invest$	0.07205			-0.69312	0.83323
$\Delta \ln lcbac$	-0.017592			-0.44282	0.63923
$\Delta \ln loaninv$	0.93497	-0.99857	1	-0.99859	0*
$\Delta \ln loans$	1.0237			-0.99915	0.021859
$\Delta \ln ollac$	0.62066			-0.17756	0.28383
$\Delta \ln olrac$	0.39323			-0.70792	0.766
$\Delta \ln \mathrm{real}$	0.75587			0.6312	0.036107
$\Delta \ln m4$	-0.017237			-0.54596	0.63936
$\Delta \ln ff$	0.00033159			0.99906	0.0028935

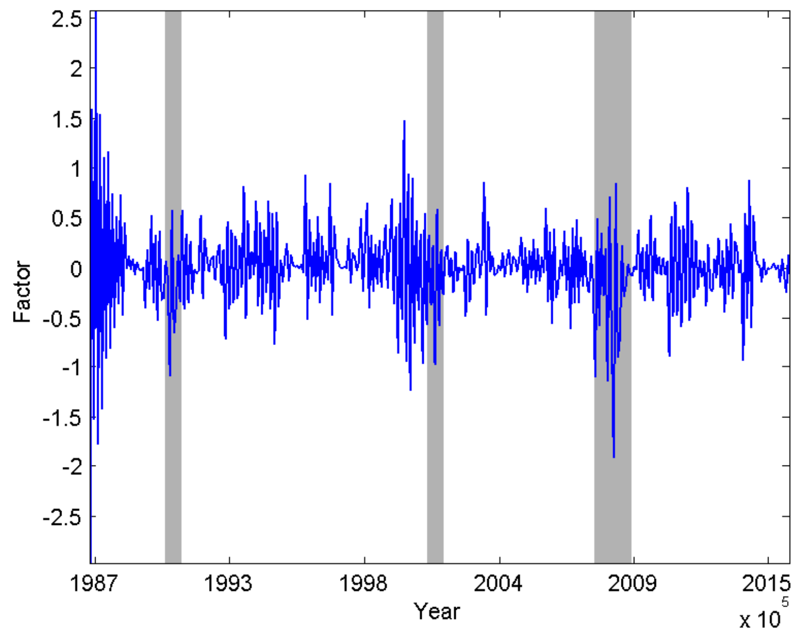

Figure 1: Estimated factor from quarterly indicators.

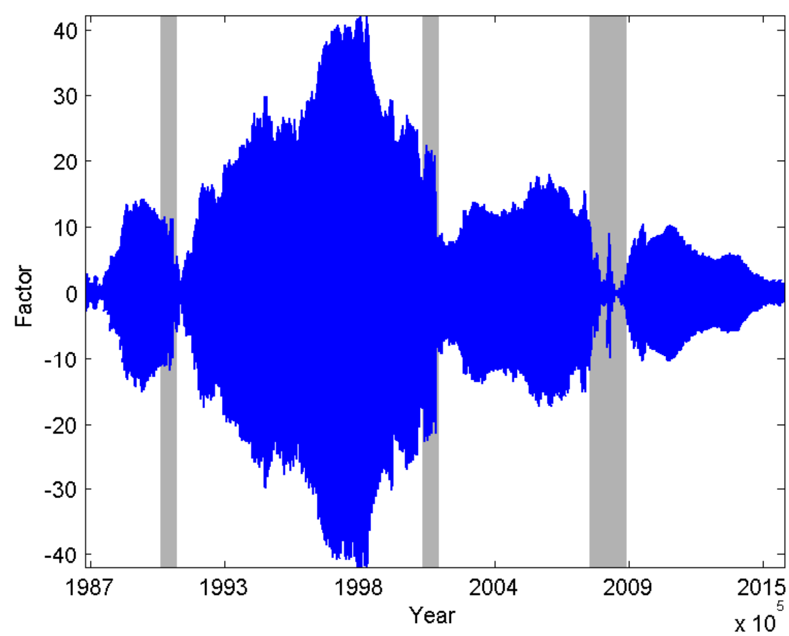

Figure 2: Estimated factor from monthly indicators.

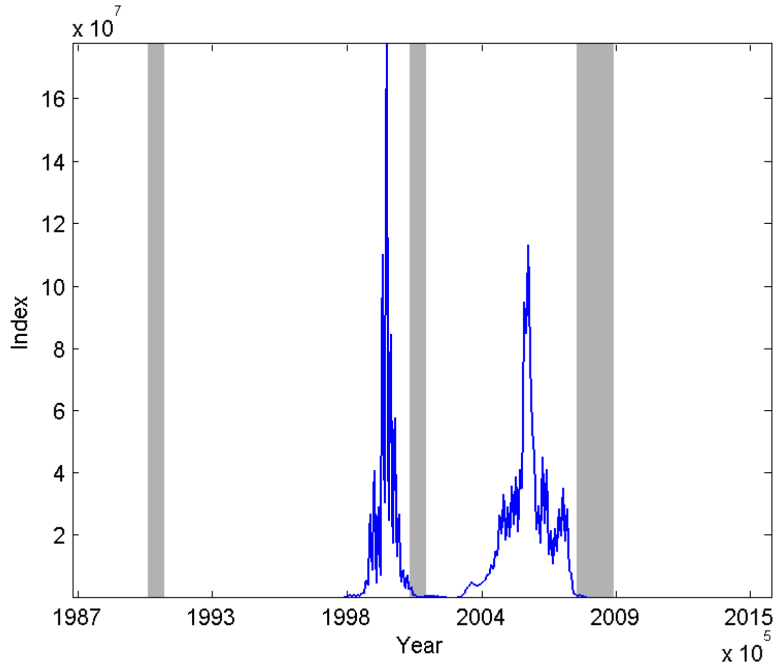

Figure 3: Coincident index constructed using quarterly indicator factor.

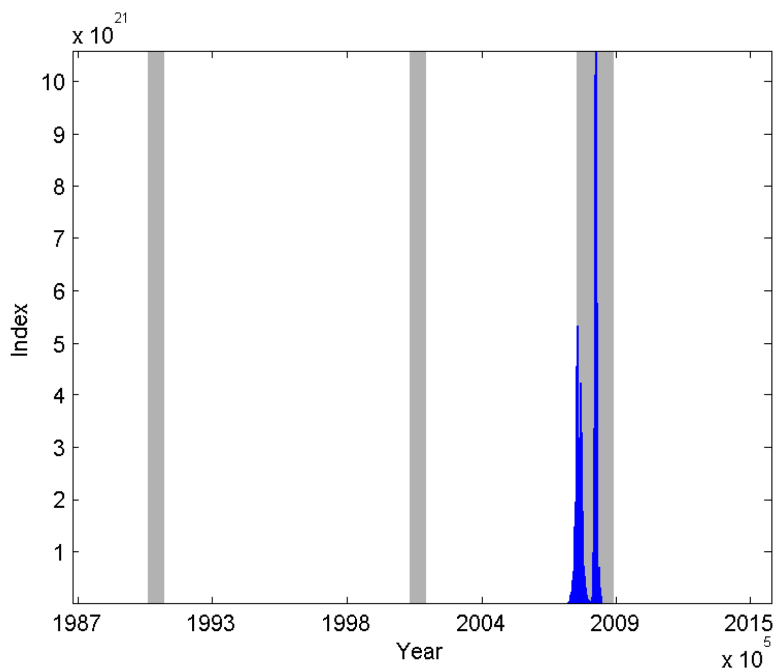

Figure 4: Coincident index constructed using the monthly indicator factor.

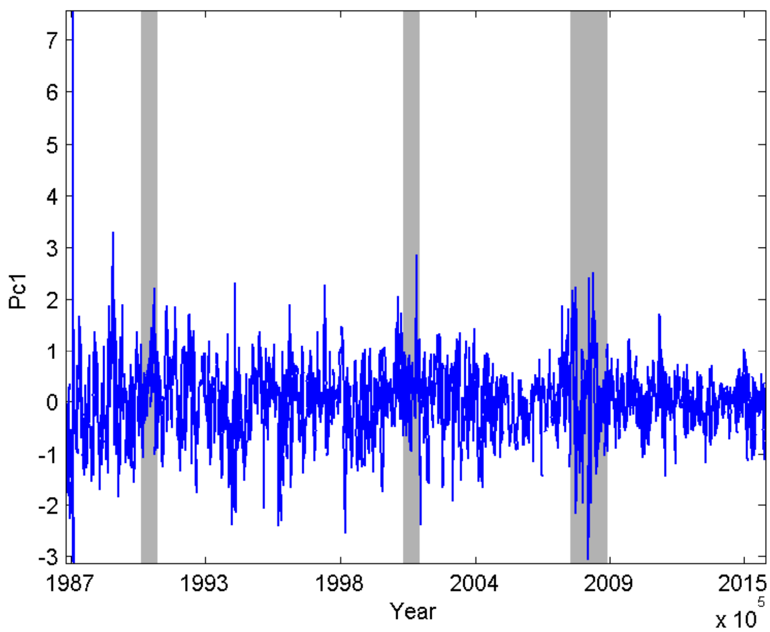

Figure 5: First principal component of weekly indicators.

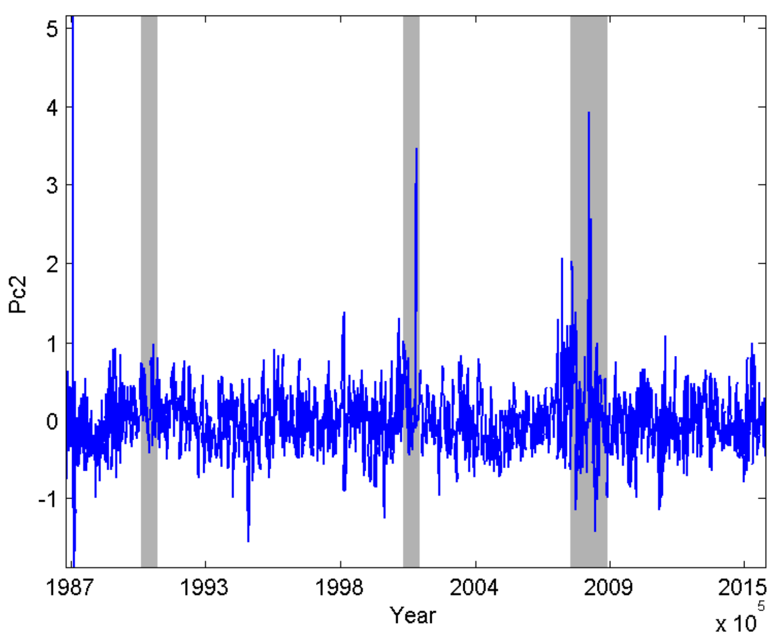

Figure 6: Second principal component of weekly indicators.

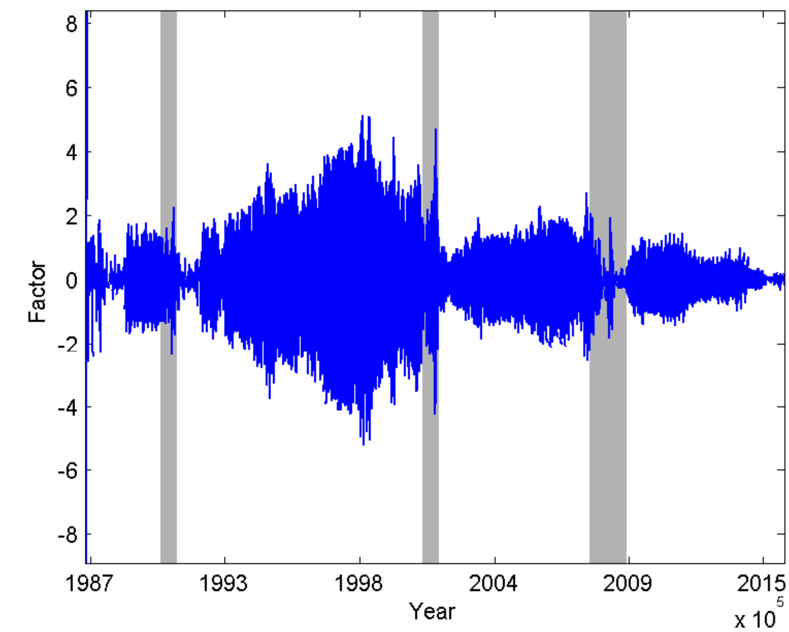

Figure 7: Estimated factor of monetary linkage.

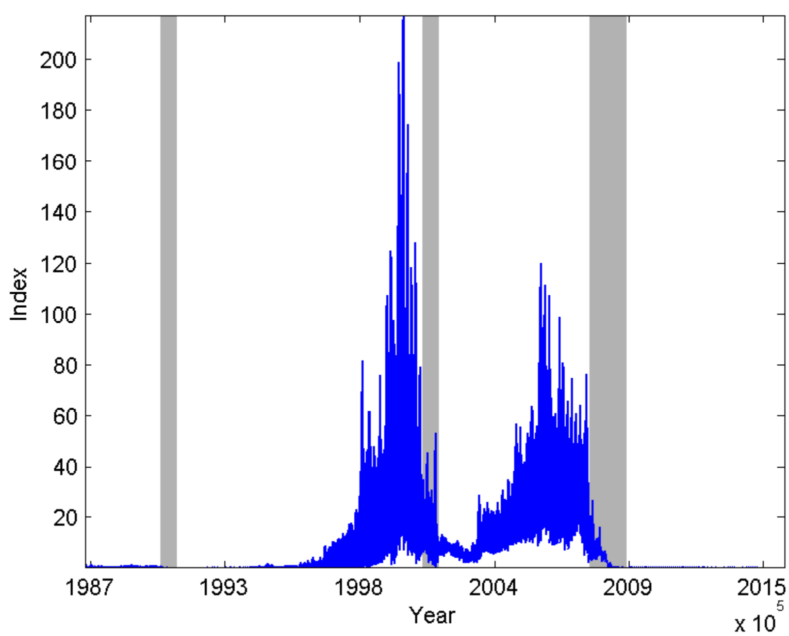

Figure 8: Coincident index constructed using estimated monetary linkage factor.

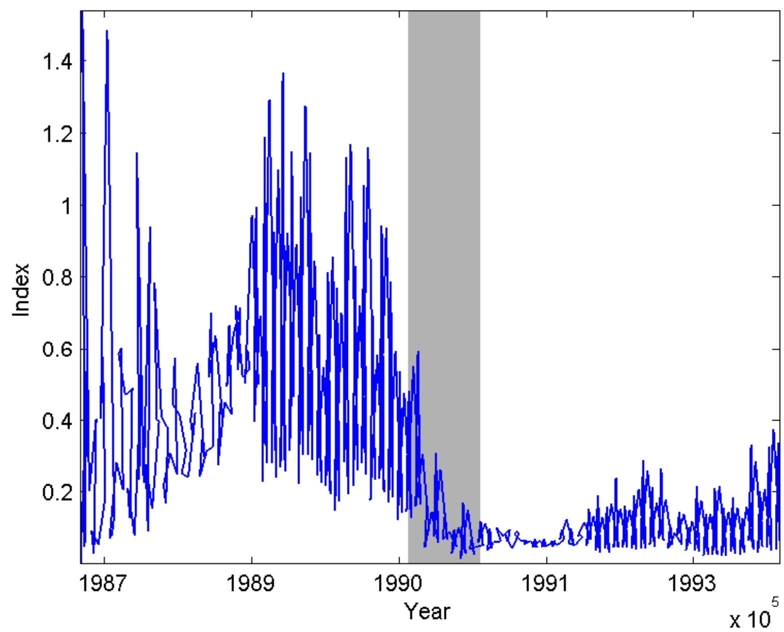

Figure 9: Coindent index in the period of 1987Q3 - 1993Q4.

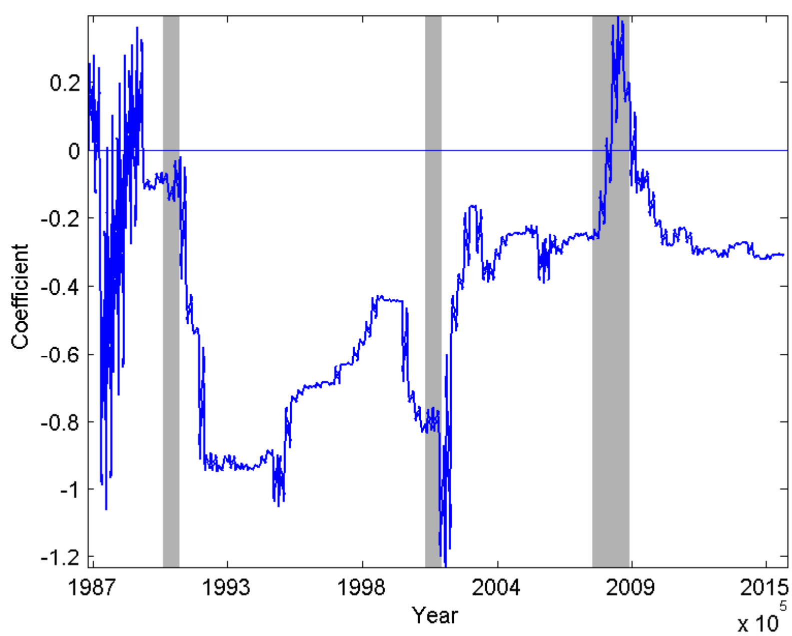

Figure 10: Estimated time-varing coefficient of monetary policy tool.