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Using Financial Markets To Estimate the Macro Effects of Monetary Policy: An Impact-Identified FAVAR*

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Abstract

In this paper, I use high-frequency financial market estimates to identify the monetary policy shock in a non-recursive 133 variable FAVAR. All restrictions are imposed exclusively on impact, and only on financial market variables. Using the economy's underlying factor structure as the link between its real and financial sides, I find that high-frequency responses contain valuable information about the behavior of lower-frequency macro variables. Even though the proposed identification scheme does not fall back on any of the standard (FA)VAR identifying assumptions, it confirms the classical finding that monetary policy has strong and significant delayed effects on real activity. I also obtain stock market responses that are compatible with the efficient market hypothesis and find that consumer prices react very little to monetary policy.

Keywords: Monetary Policy, Impact Identification, FAVAR, Financial Markets, Efficient Market Hypothesis

JEL classification: E52, E58, E44.

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1 Introduction

> "If all goes as planned, the changes in financial asset prices and returns induced by the actions of monetary policymakers lead to the changes in economic behavior that the policy was trying to achieve".
>
> Ben S. Bernanke, London School of Economics Public Lecture (2003)

It is widely believed that monetary policy affects both the real and financial sides of the economy, but actual estimation of these effects must carefully take the endogeneity of policy decisions into account. I solve this identification problem in a FAVAR framework, using only a small number of contemporaneous restrictions on financial market variables. These restrictions are directly visible in separate high-frequency estimates and carry over to lower frequencies by the logic of the efficient market hypothesis (EMH) as defined in Fama (1970).[1] One major advantage of the approach presented in this paper is that it does not require any theory-based assumptions about how macro variables interact with monetary policy. Therefore, it can serve as a cross-check for much of the existing empirical literature on the macro effects of monetary policy. In terms of results, I find strong delayed effects on real variables such as housing starts, employment and industrial production. Consumer prices, on the other hand, appear to be almost unaffected by monetary policy shocks. Furthermore, unlike the benchmark recursive FAVAR estimated as in Bernanke et al (2005), the method proposed in this paper delivers financial market responses that are compatible with the EMH.

The fundamental motivation for this paper stems from two main points. First, causal estimates of financial market responses to monetary policy can be credibly estimated by considering only those very short time-periods at which monetary policy shocks are actually known to arrive. Second, at least some of the fundamental underlying forces that drive the dynamics of financial markets may also matter for the real side of the economy.[2] Together, these two points suggest that response estimates of low-frequency macro variables may benefit from the information contained in their financial-market counterparts. In other words, if some fundamental factors matter for both financial and real variables, it should in principle be possible to exploit that overlap.

Existing work contains overwhelming empirical support for such a close relationship between the real and financial sides of the economy: First, an extensive high-frequency literature unanimously shows that financial market variables immediately react to the arrival of monetary policy and other macro news.[3] Second, it has been shown that the use of daily financial market data can actually improve the quality of macro forecasts.[4] Third, a number of studies have even shown which financial instruments contain information about which macro economic concepts.[5] In spite of this very clear picture, only a few empirical studies on the real effects of monetary policy actually recognize the additional information provided by financial markets. Three of the earliest and probably most important examples of this relatively small group of papers are Bagliano and Favero (1999), Faust et al (2003) and Faust et al (2004). All of these studies use high-frequency data to construct financial market shocks outside of the VAR framework. Then, in a second step, they use this information within a vector autoregression. In related work, Cochrane and Piazzesi (2002) construct monetary policy shocks from high-frequency data and carefully compare them to those obtained using traditional VAR methods. D'Amico and Farka (2011) use high-frequency data to allow for contemporaneous feedback between monetary policy and the stock market in an otherwise recursive VAR.[6] Finally, in very recent work, Francis et al (2011) use a variation of the MIDAS VAR framework of Ghysels (2011) to estimate structural impulse responses to monetary policy shocks.

The work presented in this paper is closely related to the above studies in that it explicitly recognizes and exploits the link between high-frequency financial market data and the real economy. However, moving beyond small-scale VARs such as Bagliano and Favero (1999) and D'Amico and Farka (2011), it uses a number of high-frequency estimates to identify the monetary policy shock in a 133 variable non-recursive FAVAR. In this context, a major advantage of the FAVAR framework is that it can include and thus restrict a relatively large number of financial variables without causing degrees of freedom issues. This is crucial because different financial variables are likely to contain information about different underlying economic factors. In addition, the use of several financial market restrictions implies that each one of them need only be implemented

[1] More precisely, I will argue below that unless market participants can regularly earn risk-adjusted excess returns by timing the market, there is a tight correspondence between daily and monthly responses to monetary policy shocks. A recent review of the empirical EMH literature is provided in Lim and Brooks (2011).

[2] For example, such factors may include both realizations and expectations of general economic activity, unemployment, real rates and inflation.

[3] Some important papers of this very large literature are Cook and Hahn (1989), Kuttner (2001), Rigobon and Sack (2004), Bernanke and Kuttner (2005), Faust et al (2007), Beechey and Wright (2009) and Ammer and Wongswan (2010).

[4] Andreou et al (2013).

[5] For example, Estrella and Hardouvelis (1991) document that the term structure predicts real activity, Gürkaynak et al (2010) extract inflation expectations from the TIPS yield curve, and Kueng (2012) shows that municipal bond spreads contain information about actual and expected federal taxes.

[6] The work of Rigobon and Sack (2003, 2004) provides strong support for such a bidirectional relationship. In an alternative approach, Bjornland and Leitemo (2009) impose a combination of long- and short-run restrictions to allow for a similar relationship without actually using high-frequency data.

in a relatively weak manner. Instead of exact point restrictions, sign or range requirements will generally turn out to be sufficient for identification. This makes the resulting structural FAVAR very robust to uncertainty in the high-frequency estimates. As a positive side effect, the approach used in this paper also allows for the inclusion of standard theory-based restrictions on macro variables and inherits the general advantages of the FAVAR framework.[7] It yields impulse responses for all 133 series included in the model and alleviates the omitted variables bias that may occur in non-factor VARs. Crucially, the financial market restrictions forming the backbone of the proposed identification scheme are directly visible in separate high-frequency estimates, highly robust to different specifications and strongly supported by economic theory.

The rest of this paper is structured as follows. Section 2 presents the econometric framework and discusses the identification approach in detail. Section 3 introduces the dataset, and section 4 contains the main empirical results. Section 5 concludes.

2 Framework and Identification

The estimation and identification of the monetary-policy FAVAR proceeds in the following three steps:

1. Estimate the responses of financial market variables to monetary policy shocks using high-frequency data.
2. Estimate a reduced form monthly FAVAR that contains the same financial market variables.
3. Use the financial-market properties obtained in step 1 to identify the monetary policy shock in the reduced form FAVAR

In this section, I explain and discuss each one of these steps in detail.

2.1 High-Frequency Estimation This first step of the estimation procedure exploits high-frequency identification methods to establish how financial market variables react to monetary policy surprises. The results obtained here form the basis of the restrictions used to identify the FAVAR below. Methodologically, the estimation closely follows a large established literature on the financial market effects of monetary policy.[8] First, I choose the high-frequency sample such that it only includes short time periods around FOMC meetings. This ensures that much of the variation in the sample is indeed driven by shocks to monetary policy. Second, I use survey data to disentangle expected from unexpected policy actions and keep only the latter as my explanatory variable. One important reason for this step is that unexpected policy components are unlikely to be correlated with potentially omitted variables.[9] Assuming that the chosen time-interval around the FOMC policy meetings spans exactly one day, the main high-frequency regression can then be written as

$$r_d^i = \alpha^i + \beta^i s_d + \epsilon_d^i \tag{1}$$

Here, r_d^i is the return of asset i on day d, s_d is the corresponding policy surprise, and β^i is asset i's monetary policy reaction coefficient.[10] As mentioned above, only days on which FOMC meetings took place are actually included in the sample. While the existing literature uses many closely related variations of this regression, the resulting estimates are generally very similar across different specifications.

2.2 FAVAR Estimation The second main element of the approach presented in this paper is the reduced-form FAVAR. Using the financial estimates from above, this FAVAR will be given a structural interpretation in the third and last step of the estimation procedure. Since the econometric framework is standard, I present only a brief review. Readers interested in a more detailed discussion may want to refer to original papers of Bernanke et al (2005) and Boivin et al (2009). First, assume that the economy is fundamentally driven by the observable monetary policy rate I_t and a relatively small number K of unobserved factors F_t. Then, let the joint law of motion of these factors be given by the following reduced form VAR

$$C_t = \Phi(L)C_{t-1} + v_t \tag{2}$$

, with

$$C_t = \begin{bmatrix} F_t \\ I_t \end{bmatrix} \tag{3}$$

[7]See Bernanke et al (2005) and Boivin et al (2009) for general discussions of the FAVAR framework.

[8]For example Cook and Hahn (1989), Kuttner (2001), Rigobon and Sack (2004), Bernanke and Kuttner (2005), Faust et al (2007), Beechey and Wright (2009) and Ammer and Wongswan (2010).

[9]Ehrmann and Fratzscher (2004) provide evidence for this.

[10]The policy surprise is defined as the difference between actual and expected policy actions. Expectations of monetary policy are derived either from surveys or from Eurodollar futures as discussed below. For the estimation, I chose a SUR framework to exploit cross-equation correlations between the error terms in (1).

and v_t being i.i.d zero-mean innovations with covariance matrix Ω. Finally, assume that all of the variables contained in the FAVAR dataset X are related to the 1

$$X_t = \Lambda C_t + e_t \tag{4}$$

Here, Λ is an N by $(K+1)$ matrix of factor loadings and e_t is a vector of series specific disturbances. In terms of interpretation, ΛC_t denotes what is typically called the *common component* of X_t, whereas e_t represents the *series-specific component*. To obtain an estimate $\hat{F}_t$ of the unobserved factors F_t, I simply regress the full dataset X_t on the monetary policy instrument I_t and then extract the first K principal components from the resulting residual series.[11] Using this factor estimate $\hat{F}_t$, the transition equation (2) can be estimated by OLS. To take estimation uncertainty in the factors and the VAR into account, I perform the same two-stage bootstrap procedure used in Boivin et al (2009). Finally, for a direct comparison to the standard recursive FAVAR identification scheme, I also compute alternative factors following Bernanke et al (2005).[12]

2.3 FAVAR Identification Having estimated both the high-frequency responses of financial market variables and the reduced-form FAVAR, I can combine the two in order to identify the monthly-frequency monetary policy shock. This is the crucial step that exploits the knowledge gained from high-frequency data to estimate structural responses of lower-frequency macro variables. I begin by imposing that the FAVAR and the high-frequency responses of financial variables are generally consistent. For example, if the identified high-frequency response of the S&P500 to a monetary tightening is a quick and permanent drop, the corresponding FAVAR response should probably not be flat or positive. Then, as a second step, I can exploit the fact that the FAVAR's underlying factors govern not only the dynamics of the financial series, but also those of the low-frequency real variables. Using equation (4) to link high-frequency and low-frequency variables allows me to recover indirect restrictions on the real side that are implied by the separately observed high-frequency restrictions on the financial side. Thus, if we are very confident about the financial variable restrictions, we can also be confident about the resulting responses of the real variables. In terms of technical implementation, I use a factor generalization of the standard sign/range restriction approach to impose the desired restrictions on the financial variables.[13] The exact procedure is described in algorithm 1 and performed on each one of the reduced-form bootstrap draws. To obtain impulse response quantiles, I follow the conventional approach of sorting the obtained IRFs at each horizon and then selecting the desired quantiles.[14] In theory, there may be other structural shocks that also satisfy the restrictions imposed in the analysis below, but that does not change the interpretation of the results in terms of monetary policy. Whether or not the obtained confidence bands also contain responses to alternative structural shocks, it is correct to interpret them as a region in which the monetary policy responses lie with a given level of confidence. Thus, while we cannot exclude the theoretical possibility that there are other structural shocks that generate similar response patterns, we do still correctly identify the properties of the monetary policy responses.

Algorithm 1 Imposing High-Frequency Restrictions on the FAVAR

1. Orthogonalize the estimated VAR in the factors denoting the structural matrix $\hat{\phi}$.
2. Obtain a quadratic matrix Z of dimension $(K+1)$, where each element $Z_{i,j}$ is drawn from an independent standard normal distribution.
3. Obtain the QR decomposition of Z such that $Z = QR$ and $Q'Q = I_{K+1}$
4. Obtain the contemporaneous factor impulse responses for the current identification draw Q as $Q\hat{\phi}$.
5. Calculate contemporaneous impulse responses of the restricted variables using observation equation (2)
6. Accept the current draw of Q if and only if these impulse responses satisfy the desired restrictions. Otherwise go back to step 1.

2.4 Identifying Assumptions The identification scheme proposed in this paper is valid if the following two conditions are satisfied: First, the estimated high frequency responses must correctly reflect those features of their true counterparts that

[11] All series in X_t are transformed for stationarity as documented in the appendix and initially normalized to have a standard deviation of 1.

[12] The classification of variables into the slow- and fast-moving categories is reported in the data appendix.

[13] For a review of this approach see, for example, Fry and Pagan (2011)

[14] Fry and Pagan (2011) argue that this approach is somewhat problematic since there may in fact not be one single identification draw and thus underlying model that yields this specific quantile. Their argument is theoretically valid, but Canova and Paustian (2011) also show that the measure of Fry and Pagan (2011) does not generally perform better in recovering the true impulse responses. I decide to use the standard approach for reasons of comparability and in order to be able to focus on the effects of the high-frequency identifying restrictions.

are used as FAVAR restrictions. Second, these features must also hold at the monthly frequency. In the following, I briefly discuss both of these conditions and why they are likely to hold.

Condition 1: Similarity Between the True and Estimated High-Frequency Responses

Since the identification approach outlined above does not use exact high-frequency point estimates, it also does not require them to be exactly identical to their true values. Instead, the estimated responses need only be correct in terms of those features that are actually used as a criterion in the FAVAR identification. For example, if we estimate a negative stock market response to a monetary tightening and impose this property in terms of a sign restriction in the FAVAR, then the approach merely requires that the true high-frequency response indeed be negative. To ensure that condition 1 holds, the implementation below uses only high-frequency restrictions that are robust to variations in data frequency, surprise measures and fundamental identifying assumptions.[15] In addition, as will be discussed in section 4.2, all of the restrictions used in this paper are also strongly supported by standard economic theory.

Condition 2: Similarity Between the High-Frequency and Monthly-Frequency Responses

The second main assumption of the proposed identification scheme is that the properties derived from high-frequency estimates carry over to monthly-frequency data. To see the correspondence between monthly and daily responses formally, consider the financial market series X^i and its month-t realization X^i_t. This realization can be expressed in terms of the previous month's value and the daily returns during the month:

$$X^i_t = X^i_{t-1} * \prod_{d=1}^{D} R^i_d \tag{5}$$

Here, R^i_d is the daily return of series X^i_t on day d of month t, and D is the last day of month t. Taking the monthly return in the form of log-differences and considering the daily log-return on $d = k$ separately then yields

$$\Delta x^i_t = \sum_{d=1}^{k-1} r^i_d + r^i_k + \sum_{d=k+1}^{D} r^i_d \tag{6}$$

Now assume that a monetary policy shock arrives on day k. Clearly, this shock cannot affect any of the returns r^i_d with $d < k$, because they are already fixed at the time of its arrival. Furthermore, if the EMH holds, new information is immediately priced in and thus delayed reactions on later dates $d > k$ are also ruled out.[16] Therefore, the monthly return reaction must occur on the day of the monetary policy shock itself, via r^i_k. It is this same-day reaction that the high-frequency regressions given by equation (1) capture and that forms the basis of the monthly-frequency restrictions. The restrictions actually used for the FAVAR below will, however, be much weaker than exact equalities and thus also robust to reasonable differences between the reactions of Δx^i_t and r^i_k. For example, mild delayed financial market responses or reversals on $d > k$ that may have occurred in the specific sample will not invalidate the proposed identification scheme. Similarly, general low-frequency price predictabilities such as those discussed by Cochrane (2007) will be accommodated by the restrictions chosen below. Compared to VAR studies that use high-frequency estimates in the form of exact point restrictions, this is one of the proposed method's main advantages.[17] Section 4.2 discusses each one of the restrictions used in this paper to further clarify the argument.

2.5 Some Important Differences to Alternative Identification Schemes First, compared to the standard identification approaches used in many (FA)VARs, this study avoids restrictions that are exclusively based on economic theory and not supported by additional high-frequency evidence. For example, it does not impose a recursive ordering and also does not rely on sign-restrictions for macro variables. This is an important advantage, because it allows us to estimate responses of macro variables without prior assumptions about their behavior. For example, consider restricting prices such that they cannot increase following a monetary tightening. Even though such a no-price-puzzle restriction is in line with many standard macro models, alternative theories such as the cost-channel of monetary transmission suggest the possibility that it may not hold in the true data generating process and thus not be suitable for identification.[18] Second, compared to existing studies that use single high-frequency point estimates to identify non-factor VARs, this paper imposes several high-frequency restrictions at a weaker level. This has two important advantages. On the one hand, the weaker nature of the restrictions can make the identification remain valid even if the high-frequency policy shocks are not *exactly* identical to their lower-frequency

[15] For example, Bernanke and Kuttner (2005) perform event-study regressions, whereas Rigobon and Sack (2004) employ identification through heteroskedasticity. The identifying assumptions of these two studies are fundamentally different, but the results are not.

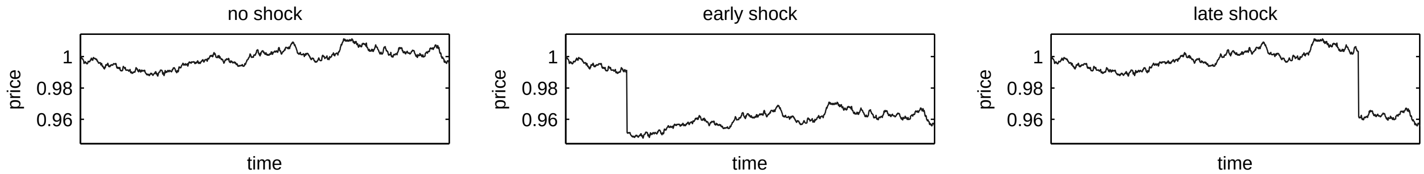
[16] See Fama (1970). If systematic delayed reactions did exist, market participants would be able to trade on them and regularly earn risk-adjusted excess returns. That, however would make them disappear.

[17] For example, D'Amico and Farka (2011).

[18] See Barth and Ramey (2001) and Chowdhury et al (2006).

counterparts.[19] On the other hand, the fact that several different financial variables can be restricted also implies that several different kinds of identifying information can be exploited. Of course, how much the imposed financial market restrictions say about the responses of different macro variables to monetary policy is directly revealed by the FAVAR results. For example, if the financial market restrictions only have power for a subset of variables, only the responses of these variables will exhibit tight confidence bands. Finally, the approach proposed in this paper also differs from the mixed-frequency method of Francis et al (2011), who focus primarily on the *timing* of policy rate innovations within the month and how these innovations can be optimally aggregated. In contrast to their approach, my method sidesteps time aggregation issues by using only general properties of financial market responses that would hold under any timing and aggregation scheme. To see this, assume as discussed above that monetary policy shocks have highly persistent level effects on financial markets that materialize within the day. Then, the timing of these shocks within the month will not affect the monthly level difference caused by the shock. Figure 1 illustrates this argument graphically.

Figure 1: Simulated Financial Market Data with Early and Late Negative Shocks



Financial market prices follow a random walk. Negative shock implemented as lower return on one specific day.

3 Data

The High-Frequency Dataset The high-frequency dataset spans the period 1994-2008 and contains daily observations of monetary policy surprises as well as a number of financial market variables.[20] As discussed above, only observations for policy days are actually used in the regressions. The main monetary policy surprise variable is defined as the difference between survey expectations and the actually realized monetary policy action.[21] For robustness, I also construct an alternative surprise measure that extracts expectations from a spliced front-month Eurodollar futures rate with a maturity of 3 months.[22] Finally, the dataset also includes the spread between the 1-year and 10-year treasury rates, the S&P 500 return, and returns on a number stock market sector series. I obtain these variables from the FRED database and the website of Kenneth French, respectively.[23]

The FAVAR Dataset The appendix contains a detailed overview of all FAVAR series and the transformations I apply for stationarity. The sample is of monthly frequency and covers the years 1973-2011. To ensure that my results are comparable to those of Bernanke et al (2005) and Boivin et al (2009), I take their datasets as reference points. The largest part of the macro series are taken from the DRI basic economics database that is also used by the authors of these two studies. While Boivin et al (2009) add several hundred disaggregated price series to their core macro dataset, I focus on financial markets. My additional variables are 30 stock market sector returns, 3 excess return variables between different stock sectors, and the 3 main measures of bank credit from the FRB H8 dataset.[24] In terms of data timing, I use monthly averages for all financial variables. This is important to ensure that the impulse responses of financial variables to monetary policy shocks have the correct magnitude. To see this, consider that a monetary policy shock occurring in the middle of the month will increase the *average* fed funds rate only by half of the shock size. If stock prices are measured in terms of end-of-the-month values, however, they will reflect the response to the full size of the shock and thus appear larger than they actually should. Using both variables in the same timing convention eliminates this inconsistency.

[19] Considering that (FA)VAR expectations are a function of monthly data whereas the high-frequency expectations condition on intra-month information, there is no obvious reason to believe and thus impose that the two should be *exactly* the same.

[20] I choose the starting date in line with the existing literature and the fact that the FOMC started openly announcing its policy decisions in 1994. The dataset does not continue beyond 2008, because my survey series ends in that year.

[21] This variable is taken directly from Kilian and Vega (2011).

[22] This second series is based on CME data and obtained via Datastream.

[23] The FRED data is available via http://research.stlouisfed.org/fred2/ and the Kenneth French data library can be accessed via http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html .

[24] It has repeatedly been argued that bank credit is an important indicator taken into consideration by the FED in its policy decisions. If that is the case, it should be included in the dataset.

4 Empirical Results

4.1 High-Frequency Results

Table 1 summarizes the estimated high-frequency responses of a number of financial market variables to a 100 basis points monetary policy shock. These responses form the basis of the restrictions imposed below to identify the monetary policy shock in the FAVAR. The regressions confirm the well-established result that financial market variables react quickly and significantly to unexpected monetary policy actions. For the stock market, they suggest a significant drop, and that the healthcare, food and utilities sectors react less than the auto sector. Furthermore, the slope of the yield-curve decreases in response to a monetary tightening. I also report the reaction coefficient of the USD/Pound exchange rate from Faust et al (2007). Their intraday analysis shows that the US Dollar appreciates relative to the Pound Sterling.[25]

Table 1: The High-Frequency Response of Financial Variables to Monetary Policy Shocks

VARIABLES	(Stock Index) S&P500	(Stock Sectors) Food-Cars	(Stock Sectors) Healthcare-Cars	(Stock Sectors) Utilities-Cars	(Yield Curve) Term Spread	(Exchange Rate) Pound/USD
Survey Shocks						
Coefficient	-7.15%***	10.33%***	8.179%***	10.22%***	-0.357***	-
Z-Statistic	(-6.176)	(7.618)	(6.264)	(6.637)	(-4.622)	-
R-squared	0.244	0.330	0.250	0.272	0.153	-
Futures Shocks						
Coefficient	-5.56%***	8.974%***	8.128%***	8.266%***	-0.353***	1.68**
Z-Statistic	(-3.505)	(4.723)	(4.694)	(3.886)	(-3.538)	n/a
R-squared	0.094	0.159	0.157	0.113	0.096	n/a
Observations	118	118	118	118	118	n/a

SUR estimates. Constant terms included but not reported. Survey Shocks defined as the difference between survey expectations and policy decisions. Futures shocks defined as changes in spliced 3-month Eurodollar futures. Term spread defined as the difference between the 10-year and 1-year treasuries. Regressions contain only one of the shock measures at a time. Exchange rate coefficient from Faust et al (2007). *** p<0.01, ** p<0.05, * p<0.1

4.2 Derived FAVAR Restrictions

Based on the high-frequency results reported in table 1, I derive the following FAVAR restrictions that are also summarized in table 2. Since financial market variables react immediately to the arrival of monetary policy news, I impose all restrictions exclusively on impact.

i) Strong Negative Response of the S&P500

First, I require that the S&P500 drops by at least 2% in response to an exogenous 100 basis points monetary tightening. While my own point estimates and those of other high-frequency studies suggest that the actual reaction is much stronger, I choose to remain relatively conservative.[26] Of course, a negative response of the stock market to an increase in interest rates is also strongly supported by theory. Discounted dividend pricing suggests a decrease in value as the discount rate increases.[27] If future dividends also decrease in response to monetary tightening, this effect becomes even stronger. Alternatively, we can think of bonds and stocks as substitutes. Then, as the monetary tightening increases the real rate on bonds, stocks should immediately become less attractive and thus exhibit a drop in prices.

ii) Strong Relative Response of the Automotive Sector

Second, I restrict the responses of the healthcare, food and utilities sectors to be less pronounced than that of the automotive industry. Again, this restriction is not only supported by the above regressions, but it is also well in line with basic economic theory. If we consider cars to be the archetypical debt-financed durable good, higher real rates should decrease their demand and thus the market valuation of the sector. On the opposite side of the spectrum, the healthcare, utilities and food sectors do not rely on debt financing in a similar fashion and should therefore not react as much. In addition, if cars are luxury goods, their sector should react more to a monetary tightening than basic goods sectors.

[25] Since exchange rate markets are particularly noisy, the use of intraday data is important for obtaining precise estimates. My high-frequency dataset is only at daily frequency, however, so I report this particular result from Faust et al (2007).

[26] Given their smaller windows around the monetary policy announcement, the confidence bands of intraday high-frequency studies are less affected by noise and therefore typically even tighter than the ones reported here.

[27] Gordon (1959).

iii) Decrease in the Slope of the Yield Curve

Third, I impose that the slope of the yield curve decreases following a monetary tightening. To see that this restriction is also strongly supported by theory, consider the expectation hypothesis of the term structure.[28] In essence, one can think of rates at the long end of the term-structure as expectations of average future short-term rates. Then, knowing that short-term rates are not perfectly persistent, the long end of the yield curve should always move less than one-for-one with monetary policy shocks occurring at the short end.[29]

iv) Appreciation of the Dollar

Fourth, I impose that the USD appreciates relative to the Pound Sterling following a monetary tightening in the US. This restriction derives additional theoretical support from theories of interest rate parity. Intuitively, if the nominal rate earned on US debt securities increases with the Federal Funds shock, then the exchange rate must slowly depreciate over time to offset this effect. Therefore, an initial appreciation must occur. Also, even if the uncovered interest rate parity relationship were not to hold in the data, an appreciation could still be explained. In the absence of a slow reversal as predicted by the UIP, it would simply be rational to invest in the currency that offers an increased return after the shock.

v) Federal Funds Range Restriction

Finally, I impose that the contemporaneous impact of a 100 basis points federal funds shock on the federal funds rate itself lies between 80 and 120 basis points. To understand this restriction, assume that the FOMC decides to increase the policy rate by 100 basis points at one of its meetings. What I require, then, is that contemporaneous relationships in the economy cannot *systematically* cause the committee to adjust this initial decision by more than 20 basis points at a later date within the month. There are two strong reasons for this restriction. First, the institutional setup of the FOMC dictates that decisions typically occur only once a month. Thus, strong systematic reversals or increases following the original decision are very unlikely. While unscheduled intra-meeting decisions do in general allow for rate changes within the month, these would still have to be strong and systematic enough to lead to a violation of the +/- 20 basis points interval that I impose. This appears very unlikely. Second, if a given interest rate decision were *generally* followed by a strong second-round increase or decrease within the month, the FOMC should become aware of this mechanism after some time and take it into account when making regular future interest rate decisions. This should then eliminate or at least strongly dampen the effect. In addition, the above argument that market participants would be able to trade against any truly systematic pattern also applies here.

vi) Optional Sign Restrictions on CPI and Industrial Production

As discussed above, one of the advantages of the identification approach presented in this paper is that the financial market impact restrictions can easily be combined with other assumptions researchers may be interested in. I make use of this option and also include additional sign restrictions on consumer prices and industrial production in a alternative identifying specification. Canova and Paustian (2011) show that these two restrictions are consistent with a large class of standard macro models, and it may therefore be particularly interesting to see how they interact with the high-frequency properties derived from the financial market estimates.[30]

Table 2: Summary of Impact Restrictions for a 100bps Shock in the Federal Funds Rate

	(1) high-frequency restrictions	(2) high-frequency and robust sign restrictions
S&P 500	$<$ -2%	$<$ -2%
Healthcare - Cars	positive	positive
Term Spread	negative	negative
USD/Pound	negative	negative
Federal Funds	80 bps $<\beta<$ 120 bps	80 bps $<\beta<$ 120 bps
CPI	-	negative
Industrial Production	-	negative

[28]See Lutz (1940) , Campbell (1986) and Cook and Hahn (1989).

[29]As discussed in Ellingsen and Söderström (2001), deflationary effects of monetary policy may even cause long-run rates to decrease after a monetary tightening. Such an inverse relationship is a particularly strong case of the restriction imposed here and therefore compatible with it. Also, any systematic effects that monetary policy may have on risk-premia along the yield curve are unlikely to be large enough on average to cause a violation of the imposed restriction.

[30]It should be noted, though, that these two additional restrictions do not form part of the novel FAVAR identification scheme proposed in this paper. There is no direct high-frequency evidence for them.

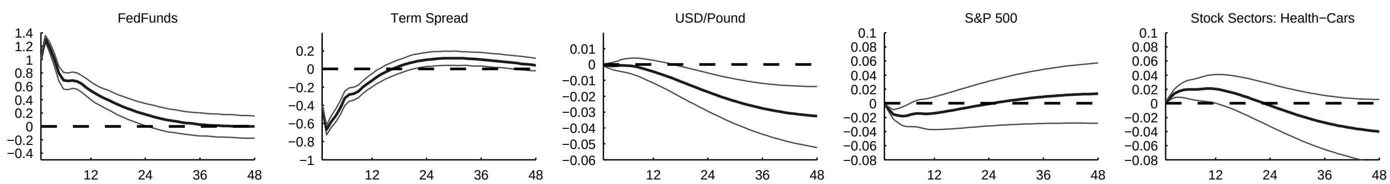
4.3 FAVAR Results

For the reduced form FAVAR, I set the number of unobservable factors to K=5 as in Bernanke et al (2005) and Boivin et al (2009). Increasing the number of factors to 6 and 7 leaves my results qualitatively unchanged and quantitatively very similar to the baseline case. The lag length of the FAVAR is set to 5, and the reported confidence bands cover the 68% range around the median at each time horizon.[31] For comparison, I also report impulse responses obtained using the standard recursive identification scheme of Bernanke et al (2005).[32] As noted above, it is generally possible that the resulting confidence areas also include responses to other structural shocks. However, this does not change the interpretation that the monetary policy responses lie within the same area at the reported confidence level.

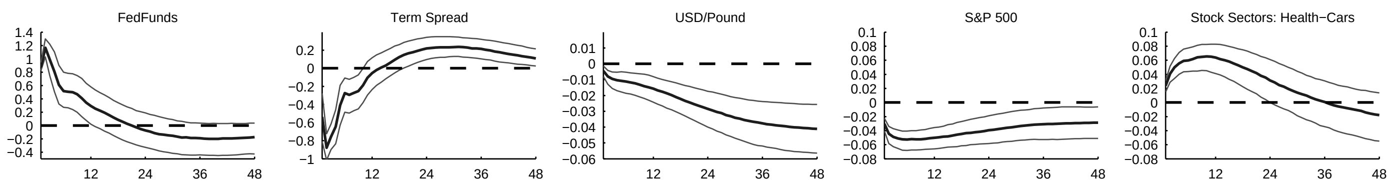
FAVAR Responses of Financial Variables For each of the 3 different identification schemes, figure 2 shows the impulse responses of 5 key financial variables to a 100 basis points shock in the federal funds rate. While the reactions of the federal funds rate and the term spread are very similar across the different identification schemes, the stock market responses clearly differ between the recursive and impact-identified versions. Instead of the instantaneous stock market reactions implied by the high-frequency results, the recursive identification shows only small delayed responses. As argued above, however, such a systematic delayed reaction contradicts the efficient market hypothesis. If it really were the true pattern, market participants could make risk-adjusted profits by trading on it. That, however, should make the pattern itself disappear.[33] The responses obtained with the identification scheme proposed in this paper, on the other hand, are well in line with the EMH: The initial reaction occurs contemporaneously and its effect is highly persistent. Even 4 years after the initial shock, the response remains significant. Importantly, this feature is a result of the identification scheme and not imposed as a restriction.

Figure 2: Monthly Financial Responses to a 100 Basis Points Monetary Policy Shock

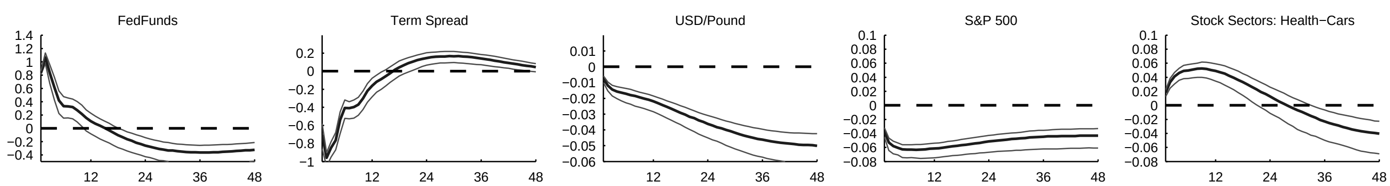
Schedule A: Standard Recursive Identification



Schedule B: Financial Market Identification



Schedule C: Financial Market and Robust Sign Restrictions



68% confidence bands based on 10 000 bootstrap draws. For schedules B and C, the bands reflect both estimation and identification uncertainty.

[31] While both Bernanke et al (2005) and Boivin et al (2009) use 13 lags, the Hannan-Quinn and Schwarz information criteria suggest that fewer lags are optimal.

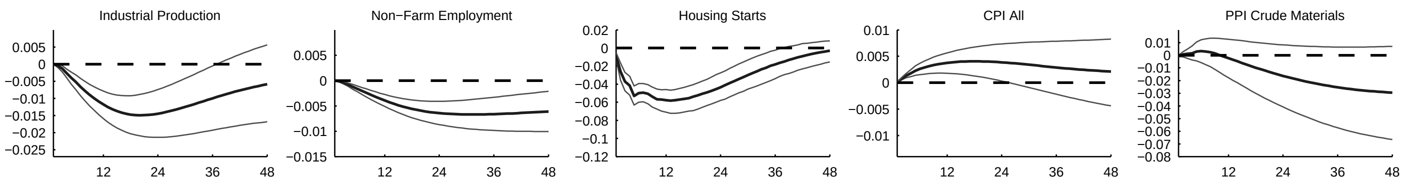
[32] The classification of variables into slow and fast groups is reported in the appendix. The results are, however, very robust to using the same factor specification in both cases.

[33] Note that the high-frequency identified stock market responses also exhibit a delay before they reach their maximum. However, this is an artefact of the financial series being expressed in terms of monthly averages. As explained above, in averaged data, any permanent shock not happening at the very beginning of the month will only reach its full level in the month that follows.

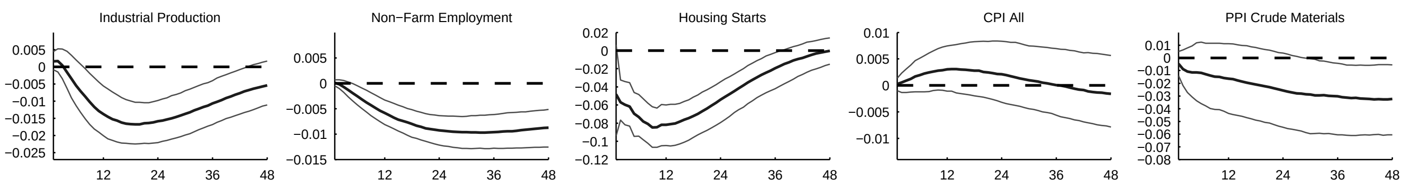
FAVAR Responses of Macro Variables Considering the responses of a number of macro variables, I find that central features obtained with the standard recursive Bernanke et al (2005) approach carry over to the fundamentally different financial market identification method. For the intermediate run, both approaches suggest that industrial production, housing starts and employment decrease. These effects come out as long-lasting and only fade away after approximately 4 years. For Consumer prices, both the recursive and financial-market FAVARs suggest a weak delayed price puzzle whereas crude material prices exhibit a slow and marginally significant decrease in both identification schemes.[34] How do these results change when we also exclude the contemporaneous price puzzle and and a positive effect on industrial production? As schedule C of figure 3 shows, the intermediate effects on employment, housing starts and industrial production remain unchanged, but we now observe continuously decreasing consumer and crude material prices.

Figure 3: Monthly Macro Responses to a 100 Basis Points Monetary Policy Shock

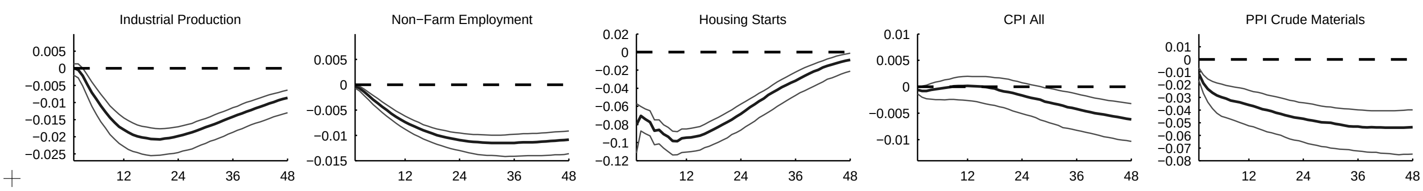
Schedule A: Standard Recursive Identification



Schedule B: Financial Market Identification



Schedule C: Financial Market and Robust Sign Restrictions



68% confidence bands based on 10 000 bootstrap draws. For schedules B and C, the bands reflect both estimation and identification uncertainty.

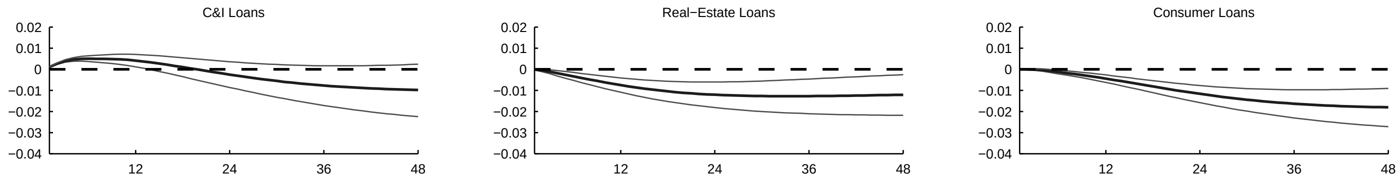
FAVAR Responses of FRB H8 Loan Volumes In the wake of the recent financial crisis, the effect of monetary policy on bank lending volumes has received particularly much attention. To shed light on this issue, I report the responses of the 3 main measures of the H8 dataset on bank lending. For all three identification schemes, my results suggest that commercial and industrial (C&I) loans increase following a monetary tightening whereas real estate and consumer loans do not. At longer horizons, all three loan measures show significant negative responses. Given how robust the initial increase in C&I loans appears to be, further work may have to address the question how it can be reconciled with standard models of the bank lending channel.[35]

[34] Bernanke et al (2005) and Boivin et al (2009) find no price puzzles. Limiting the sample period to that of Boivin et al (2009) and increasing the number of lags to 13 as in their estimates somewhat weakens the puzzle.

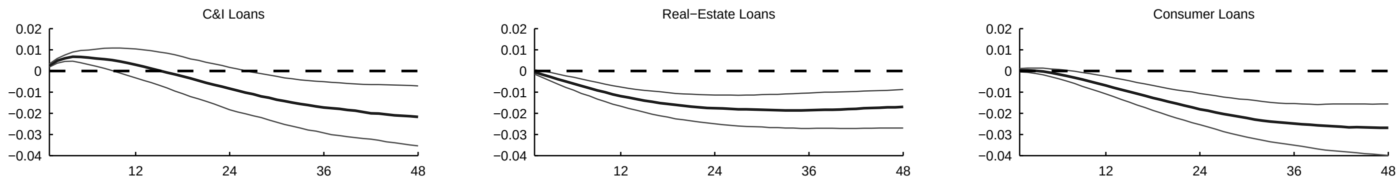
[35] Den Haan et al (2007) obtain a similar result and discuss some potential explanations.

Figure 4: FRB H8 Loan Volume Responses to a 100 Basis Points Monetary Policy Shock

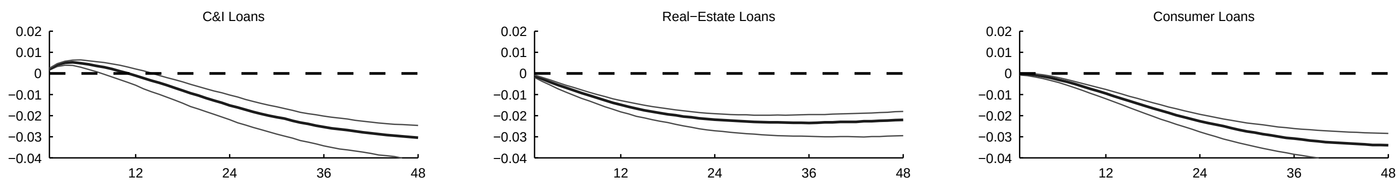
Schedule A: Standard Recursive Identification



Schedule B: Financial Market Identification



Schedule C: Financial Market and Robust Sign Restrictions



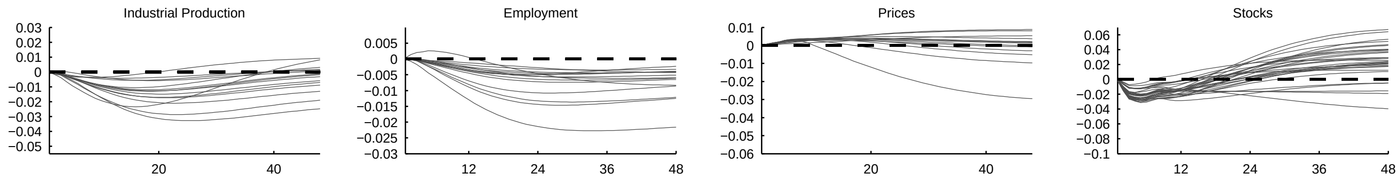
68% confidence bands based on 10 000 bootstrap draws. For schedules B and C, the bands reflect both estimation and identification uncertainty.

Response Dispersion Finally, working in the FAVAR framework, we can also look at responses of more disaggregated data series. Figure 5 shows sector responses of industrial production, employment, prices and stocks under all 3 identification schemes. The main result here is that the above findings also hold at this less aggregated level and are not just driven by single sectors. Industrial production and employment show persistent decreases in all 3 cases, and prices only exhibit very weak responses. As to the stock market, the sectoral responses show very large amounts of dispersion. This is consistent with existing sector-level high-frequency evidence.[36] However, under the recursive identification scheme every single stock sector shows a delayed response. As argued above, this strongly contradicts both theory and high-frequency estimates.

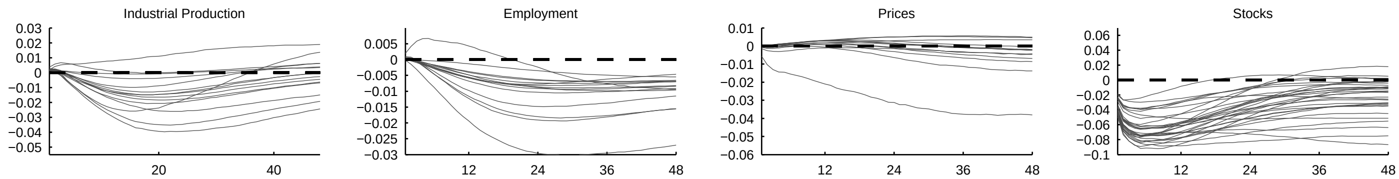
[36] For example, see Ehrmann and Fratzscher (2004).

Figure 5: Sectoral Dispersion in Monthly Responses to a 100 Basis Points Monetary Policy Shock

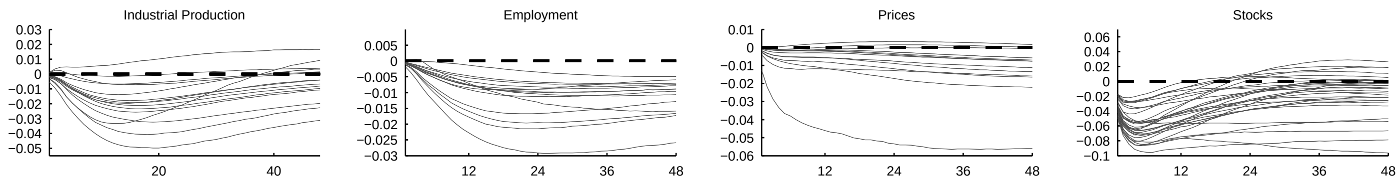
Schedule A: Standard Recursive Identification



Schedule B: Financial Market Identification



Schedule C: Financial Market and Robust Sign Restrictions



Estimates based on 10 000 bootstrap draws. Only Medians reported.

5 Concluding Remarks

This paper illustrates how high-frequency financial market estimates can be used to identify structural monetary policy responses in a complete non-recursive FAVAR. Exploiting the economy's underlying factor structure as the link between low- and high-frequency data, the proposed method confirms key results of a benchmark recursive FAVAR. More precisely, it suggests that monetary policy has significant effects on real activity and only a very limited impact on consumer prices. These findings are important, because they are obtained without falling back on *any* of the classical VAR and FAVAR identifying assumptions. In terms of financial market responses, the proposed method improves upon the benchmark recursive FAVAR in so far as it delivers responses that do not contradict the efficient market hypothesis. Considering that the EMH is one of the most widely accepted and most difficult-to-reject building blocks of modern finance, this is a desirable property. In the future, the method presented here may also be augmented with information from additional high-frequency variables. For example, as the time-series for TIPS bonds gets long enough to be included in a FAVAR, we may hope to capture inflation expectations even more precisely. Nevertheless, the results of the above analysis show that even very standard financial market variables greatly help identify the real effects of monetary policy.

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Appendix: The Series of the FAVAR Dataset

Variable Description	Name	Transformation	Fast in BBE
CONSUMER CREDIT OUTSTANDING - NONREVOLVING(G19)	CCINRV	log differences	Yes
EMPLOYEES, NONFARM - TOTAL NONFARM	CES001	log differences	No
EMPLOYEES, NONFARM - TOTAL PRIVATE	CES002	log differences	No
EMPLOYEES, NONFARM - GOODS-PRODUCING	CES003	log differences	No
EMPLOYEES, NONFARM - NATURAL RESOURCES & MINING	CES004	log differences	No
EMPLOYEES, NONFARM - CONSTRUCTION	CES011	log differences	No
EMPLOYEES, NONFARM - MANUFACTURING	CES015	log differences	No
EMPLOYEES, NONFARM - DURABLE GOODS	CES017	log differences	No
EMPLOYEES, NONFARM - NONDURABLE GOODS	CES033	log differences	No
EMPLOYEES, NONFARM - SERVICE-PROVIDING	CES046	log differences	No
EMPLOYEES, NONFARM - PRIVATE SERVICE-PROVIDING	CES047	log differences	No
EMPLOYEES, NONFARM - TRADE, TRANSPORT, UTILITIES	CES048	log differences	No
EMPLOYEES, NONFARM - WHOLESALE TRADE	CES049	log differences	No
EMPLOYEES, NONFARM - RETAIL TRADE	CES053	log differences	No
EMPLOYEES, NONFARM - FINANCIAL ACTIVITIES	CES088	log differences	No
EMPLOYEES, NONFARM - GOVERNMENT	CES140	log differences	No
AVERAGE WEEKLY HOURS, PRODUCTS WRKRS, NONFARM - TOTAL PRIVATE	CES150	as is	No
AVERAGE WEEKLY OVERTIME HOURS, PRODUCTS WRKRS, NONFARM - MANUFACTURING	CES155	as is	No
AVERAGE HRLY EARNINGS, PRODUCTS WRKRS, NONFARM - CONSTRUCTION	CES277	log differences	No
AVERAGE HRLY EARNINGS, PRODUCTS WRKRS, NONFARM - MANUFACTURING	CES278	log differences	No
MOBILE HOMES: MANUFACTURERS' SHIPMENTS (THOUS.OF UNITS,SAAR)	HMOB	logs	Yes
HOUSING AUTHORIZED: TOTAL NEW PRIV HOUSING UNITS (THOUS.,SAAR)	HSBR	logs	Yes
HOUSING STARTS:NONFARM(1947-58);TOTAL FARM&NONFARM(1959-)(THOUS.,SA	HSFR	logs	Yes
HOUSING STARTS:MIDWEST(THOUS.U.)S.A.	HSMW	logs	Yes
HOUSING STARTS:NORTHEAST (THOUS.U.)S.A.	HSNE	logs	Yes
HOUSING STARTS:SOUTH (THOUS.U.)S.A.	HSSOU	logs	Yes
HOUSING STARTS:WEST (THOUS.U.)S.A.	HSWST	logs	Yes
INDUSTRIAL PRODUCTION INDEX - TOTAL INDEX	IPS10	log differences	No
INDUSTRIAL PRODUCTION INDEX - PRODUCTS, TOTAL	IPS11	log differences	No
INDUSTRIAL PRODUCTION INDEX - CONSUMER GOODS	IPS12	log differences	No
INDUSTRIAL PRODUCTION INDEX - DURABLE CONSUMER GOODS	IPS13	log differences	No
INDUSTRIAL PRODUCTION INDEX - NONDURABLE CONSUMER GOODS	IPS18	log differences	No
INDUSTRIAL PRODUCTION INDEX - BUSINESS EQUIPMENT	IPS25	log differences	No
INDUSTRIAL PRODUCTION INDEX - FINAL PRODUCTS	IPS299	log differences	No
INDUSTRIAL PRODUCTION INDEX - RESIDENTIAL UTILITIES	IPS307	log differences	No
INDUSTRIAL PRODUCTION INDEX - BASIC METALS	IPS316	log differences	No
INDUSTRIAL PRODUCTION INDEX - MATERIALS	IPS32	log differences	No
INDUSTRIAL PRODUCTION INDEX - DURABLE GOODS MATERIALS	IPS34	log differences	No
INDUSTRIAL PRODUCTION INDEX - NONDURABLE GOODS MATERIALS	IPS38	log differences	No
INDUSTRIAL PRODUCTION INDEX - MANUFACTURING (SIC)	IPS43	log differences	No
INDUSTRIAL PRODUCTION INDEX - MINING NAICS=21	IPS67	log differences	No
INDUSTRIAL PRODUCTION INDEX - ELECTRIC AND GAS UTILITIES	IPS68	log differences	No
CIVILIAN LABOR FORCE: EMPLOYED, TOTAL (THOUS.,SA)	LHEM	log differences	No
CIVILIAN LABOR FORCE: EMPLOYED, NONAGRIC.INDUSTRIES (THOUS.,SA)	LHNAG	log differences	No
UNEMPLOY.BY DURATION: PERSONS UNEMPL.5 TO 14 WKS (THOUS.,SA)	LHU14	as is	No
UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 WKS + (THOUS.,SA)	LHU15	as is	No
UNEMPLOY.BY DURATION: PERSONS UNEMPL.15 TO 26 WKS (THOUS.,SA)	LHU26	as is	No
UNEMPLOY.BY DURATION: PERSONS UNEMPL.LESS THAN 5 WKS (THOUS.,SA)	LHU5	as is	No
UNEMPLOY.BY DURATION: AVERAGE(MEAN)DURATION IN WEEKS (SA)	LHU680	as is	No
UNEMPLOYMENT RATE: ALL WORKERS, 16 YEARS & OVER (%,SA)	LHUR	as is	No

Variable Description	Name	Transformation	Fast in BBE FAVAR
NEW ORDERS (NET) - CONSUMER GOODS & MATERIALS, 1996 DOLLARS (BCI)	MOCMQ	log differences	Yes
NEW ORDERS, NONDEFENSE CAPITAL GOODS, IN 1996 DOLLARS (BCI)	MSONDQ	log differences	Yes
NAPM COMMODITY PRICES INDEX (PERCENT)	PMCP	as is	Yes
NAPM VENDOR DELIVERIES INDEX (PERCENT)	PMDEL	as is	Yes
NAPM EMPLOYMENT INDEX (PERCENT)	PMEMP	as is	No
PURCHASING MANAGERS' INDEX (SA)	PMI	log differences	No
NAPM NEW ORDERS INDEX (PERCENT)	PMNO	as is	Yes
NAPM INVENTORIES INDEX (PERCENT)	PMNV	as is	Yes
NAPM PRODUCTION INDEX (PERCENT)	PMP	log differences	No
CPI-U: APPAREL & UPKEEP (82-84=100,SA)	PU83	log differences	No
CPI-U: TRANSPORTATION (82-84=100,SA)	PU84	log differences	No
CPI-U: MEDICAL CARE (82-84=100,SA)	PU85	log differences	No
CPI-U: COMMODITIES (82-84=100,SA)	PUC	log differences	No
CPI-U: DURABLES (82-84=100,SA)	PUCD	log differences	No
CPI-U: ALL ITEMS (82-84=100,SA)	PUNEW	log differences	No
CPI-U: ALL ITEMS LESS FOOD (82-84=100,SA)	PUXF	log differences	No
CPI-U: ALL ITEMS LESS SHELTER (82-84=100,SA)	PUXHS	log differences	No
CPI-U: ALL ITEMS LESS MIDICAL CARE (82-84=100,SA)	PUXM	log differences	No
PRODUCER PRICE INDEX:CRUDE MATERIALS (82=100,SA)	PWCMSA	log differences	No
PRODUCER PRICE INDEX:FINISHED CONSUMER GOODS (82=100,SA)	PWFCSA	log differences	No
PRODUCER PRICE INDEX: FINISHED GOODS (82=100,SA)	PWFSA	log differences	No
PRODUCER PRICE INDEX:INTERMED MAT.SUPPLIES & COMPONENTS(82=100,SA)	PWIMSA	log differences	No
PERSONAL INCOME (CHAINED) (BIL2000$,SAAR)	YPR	log differences	No
MONEY STOCK: M1(CURR,TRAV.CKS,DEM DEP,OTHER CK'ABLE DEP)(BIL$,SA)	FM1	log differences	Yes
MONEY STOCK:M2(M1+O'NITE RPS,EURO$,G/P&B/D MMMFS&SAV&SM TIME DEP(BIL$,	FM2	log differences	Yes
MONETARY BASE, ADJ FOR RESERVE REQUIREMENT CHANGES(MIL$,SA)	FMFBA	log differences	Yes
DEPOSITORY INST RESERVES:TOTAL,ADJ FOR RESERVE REQ CHGS(MIL$,SA)	FMRRA	log differences	Yes
FOREIGN EXCHANGE RATE: CANADA (CANADIAN $ PER U.S.$)	DEXCAUS	log differences	Yes
FOREIGN EXCHANGE RATE: JAPAN (YEN PER U.S.$)	DEXJPUS	log differences	Yes
FOREIGN EXCHANGE RATE: SWITZERLAND (SWISS FRANC PER U.S.$)	DEXSZUS	log differences	Yes
FOREIGN EXCHANGE RATE: UNITED KINGDOM (CENTS PER POUND)	DEXUSUK	log differences	Yes
INTEREST RATE: FEDERAL FUNDS (EFFECTIVE) (% PER ANNUM,NSA)	DFF	as is	Yes
INTEREST RATE: U.S.TREASURY CONST MATURITIES,1-YR.(% PER ANN,NSA)	DGS1	as is	Yes
INTEREST RATE: U.S.TREASURY CONST MATURITIES,10-YR.(% PER ANN,NSA)	DGS10	as is	Yes
INTEREST RATE: U.S.TREASURY CONST MATURITIES,5-YR.(% PER ANN,NSA)	DGS5	as is	Yes
INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,3-MO.(% PER ANN,NSA)	DTB3	as is	Yes
INTEREST RATE: U.S.TREASURY BILLS,SEC MKT,6-MO.(% PER ANN,NSA)	DTB6	as is	Yes
S&P'S COMMON STOCK PRICE INDEX: COMPOSITE (1941-43=10)	SP500	log differences	Yes
Spread DGS1 - DFF	SPRDGS1	as is	Yes
Spread DGS10 - DFF	SPRDGS10	as is	Yes
Spread DGS5 - DFF	SPRDGS5	as is	Yes
Spread TB3M - DFF	SPRTB3	as is	Yes
Spread TB6M - DFF	SPRTB6	as is	Yes
Spread WAAA - DFF	SPRWAAA	as is	Yes
Spread WBAA - DFF	SPRWBAA	as is	Yes
BOND YIELD: MOODY'S AAA CORPORATE (% PER ANNUM)	WAAA	as is	Yes
BOND YIELD: MOODY'S BAA CORPORATE (% PER ANNUM)	WBAA	as is	Yes
FRB H8 Commercial and Industrial Loans - All Bank - Seasonally Adjusted	H8CIL	log differences	Yes
FRB H8 Consumer Loans - All Bank - Seasonally Adjusted	H8COL	log differences	Yes
FRB H8 Real Estate Loans - All Bank - Seasonally Adjusted	H8REL	log differences	Yes

Variable Description	Name	Transformation	Fast in BBE FAVAR
Food Products	Stocks1	log differences	Yes
Textiles	Stocks10	log differences	Yes
Construction and Construction Materials	Stocks11	log differences	Yes
Steel Works Etc	Stocks12	log differences	Yes
Fabricated Products and Machinery	Stocks13	log differences	Yes
Electrical Equipment	Stocks14	log differences	Yes
Automobiles and Trucks	Stocks15	log differences	Yes
Aircraft, ships, and railroad equipment	Stocks16	log differences	Yes
Precious Metals, Non-Metallic, and Industrial Metal Mining	Stocks17	log differences	Yes
Coal	Stocks18	log differences	Yes
Petroleum and Natural Gas	Stocks19	log differences	Yes
Beer & Liquor	Stocks2	log differences	Yes
Utilities	Stocks20	log differences	Yes
Communication	Stocks21	log differences	Yes
Personal and Business Services	Stocks22	log differences	Yes
Business Equipment	Stocks23	log differences	Yes
Business Supplies and Shipping, Containers	Stocks24	log differences	Yes
Transportation	Stocks25	log differences	Yes
Wholesale	Stocks26	log differences	Yes
Retail	Stocks27	log differences	Yes
Restaraunts, Hotels, Motels	Stocks28	log differences	Yes
Banking, Insurance, Real Estate, Trading	Stocks29	log differences	Yes
Tobacco Products	Stocks3	log differences	Yes
Everything Else	Stocks30	log differences	Yes
Recreation	Stocks4	log differences	Yes
Printing and Publishing	Stocks5	log differences	Yes
Consumer Goods	Stocks6	log differences	Yes
Apparel	Stocks7	log differences	Yes
Healthcare, Medical Equipment, Pharmaceutical Products	Stocks8	log differences	Yes
Chemicals	Stocks9	log differences	Yes
Excess Return: Healthcare, Medical Equipment, Pharmaceutical Products - Automobiles and Trucks	StockSpread1	log differences	Yes
Excess Return: Food Products - Automobiles and Trucks	StockSpread2	log differences	Yes
Excess Return: Utilities - Automobiles and Trucks	StockSpread3	log differences	Yes

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