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The Low-Frequency Impact of Daily Monetary Policy Shocks*

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Abstract

With rare exception, studies of monetary policy tend to neglect the timing of innovations to monetary policy instruments. Models which take timing seriously are often difficult to compare to standard monetary VARs because each uses different frequencies. We propose using MIDAS regressions that nests both ideas: Accurate (daily) timing of innovations to policy are embedded in a monthly-frequency VAR to determine the macroeconomic effects of high-frequency policy shocks. We find that policy have greatest effects on variables thought of as heavily expectations oriented and that, contrary to some VAR studies, the effects of policy shocks on real variables are small.

Keywords: monetary policy, daily fed funds rate, price puzzle, mixed data frequencies
JEL: C32, C50, E32

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1 Introduction

Since the seminal work of Sims (1980), much of the literature on monetary policy shocks and their propagation has used vector autoregression (hereafter, VAR) models with either monthly or quarterly macroeconomic time series. VAR-based identification of monetary policy shocks has been criticized for a number of reasons, both technical and philosophical. Some argue that the restrictions that identify monetary policy shocks are *ad hoc*. Others contend that VARs produce responses inconsistent with a forward-looking identification of monetary policy shocks. For example, Rudebusch (1998) demonstrates that monetary policy shocks computed using monthly federal funds futures rates are generally uncorrelated with the monetary policy shocks identified by VARs (see also Bernanke and Mihov (1998) and Christiano, Eichenbaum, and Evans (1999), henceforth CEE). Rudebusch contends that monetary policy shocks coming from the federal funds futures rates, which proxy household expectations of the monetary policy instrument in VARs, should at least be correlated with VAR monetary policy shocks, since they are the surprises that VAR shocks seek to uncover.[1]

Macroeconomic data are typically available at a quarterly or monthly frequency, while financial data, from which financial expectations can be retrieved, are available at a daily frequency. This sampling disparity causes a dilemma about whether to focus exclusively on monthly data, which is what VARs do, or on daily financial data, which is what more recent papers on monetary policy shocks have done. Some studies have suggested using the daily effective fed funds rate or the daily (or monthly) fed funds futures rate when studying monetary policy.[2] For example, Kuttner (2001) uses federal funds futures data to isolate anticipated and unanticipated components of changes in the target federal funds rate. He then examines each component's impact on bill, note, and bond yields, using and extending the approach of Cook and Hahn (1989). Cochrane and Piazzesi (2002) study monetary policy shocks defined by movements in the federal funds rate target relative to changes in the daily interest rate. They measure the unexpected target rate change in monetary policy as the change (up to two days prior) in the one-month eurodollar rate around changes in the federal funds rate target. To identify monthly monetary policy shocks Cochrane and Piazzesi *aggregate* their daily monetary policy shock series which they then compare to the Christiano, Eichenbaum, and Evans (1999) monthly monetary policy shock series.[3] Faust, Swanson, and Wright (2004) (henceforth FSW) use the fed funds futures data to identify monetary policy shocks in a VAR. They identify the surprise element in monetary policy by running a regression of the federal funds rate on the federal funds futures data. Imposing this measure of monetary surprise as the impulse response of the fed funds rate to a monetary policy shock, they then search for plausible impulse responses of other macroeconomic variables consistent with the (imposed) Fed's own response.

There is clearly a tension between the low-frequency phenomenon of the policy impact we want to measure and the availability of high-frequency (daily) data on policy surprises. The current paper

[1]Rudebusch (1998) also demonstrates that other variables that are likely to be in the Federal Reserve policy reaction function are uncorrelated with the VAR shocks.

[2]Gurkaynak, Sack, and Swanson (2007) compared the predictive ability of the federal funds futures rate to Eurodollar rates, Eurodollar futures, the Treasury bill rate, commercial paper, and term fed funds loan rate. They demonstrate that the federal funds futures rate is the best asset for forecasting the federal funds rate at horizons up to six months. At longer horizons, the noted financial assets do equally well at forecasting the federal funds rate. This implies that the federal funds futures rate does the best job at capturing monetary policy expectations.

[3]In Cochrane and Piazzesi (2002), the monthly shock equals zero in (i) months when there are no target rate changes and (ii) months where the target change is perfectly anticipated.

provides a solution to the tension of mixed sampling frequencies that makes measuring the impact of monetary policy shocks difficult.

The approach in this paper combines low-frequency macroeconomic time-series data (that record the affect of monetary policy shocks) with daily high-frequency time series data (that pertain to the timing of monetary policy shocks). We do so without imposing *a priori* aggregation schemes; in fact, we use a framework where the *data decides,* with minimal model restrictions, the *best* way to combine the different data frequencies. This methodology relies on a more parsimonious approach to regression analysis with data of different frequencies. Namely, we use so-called MIDAS, meaning Mi(xed) Da(ta) S(ampling), regressions.[4] The primary advantage of MIDAS regressions is their relative parsimony compared with models that estimate separate unconstrained parameters for (in this case) daily data.

While MIDAS regressions have been studied elsewhere extensively, the prime objective of this paper is to use such regressions to construct impulse response functions and compare them with more traditional VAR-model impulse response functions.[5] The focus on impulse response functions is natural, given that our objective is to analyze the longer-term impact of daily monetary policy shocks. In particular, we propose a model that takes into consideration the timing of the fed funds shock. Unique to our approach is the use of daily data to measure expectations and by extension innovations to monetary policy. Using this approach, we find that monetary policy surprises fail to have significant effects on real variables such as industrial production and employment. However, we find that such surprises do have significant effects on inflation expectation and delayed effects on core inflation, similar to the finding in FSW. Additionally, monetary policy surprises have a delayed effect on consumer credit and in the specification controlling for days leading up to FOMC meetings, they have significant effects on the level of consumer confidence in the economy. However, the latter finding indicates a reversal of the significant effects of monetary policy on consumer confidence in the days leading up to FOMC meetings.

The balance of the paper is organized as follows: Section 2 describes the empirical model, a modification of the standard monetary VAR which mixes both monthly and daily data. We also describe how a monetary policy shock is identified in our environment. We incorporate additional terms in our MIDAS regression to account for both the policy innovation and the days leading up to the policy decision. Finally, we also compare our shocks to those identified by standard VAR timing restrictions. Section 3 describes the data and presents the empirical results. Robustness with regards to the specification of monetary policy shocks is discussed in Section 4. Section 5 summarizes and offers conclusions.

2 High-Frequency Policy Shocks and Low-Frequency Impact: Model Specification

In this section, we present the specification of the empirical models. We start with a brief introduction of various approaches to mixed frequency data, and then identify monetary policy shocks using

[4] MIDAS regressions were suggested in recent work by Ghysels, Santa-Clara, and Valkanov (2004); Ghysels, Santa-Clara, and Valkanov (2006); and Andreou, Ghysels, and Kourtellos (2010). The initial work on MIDAS focused on volatility predictions, see also Alper, Fendoglu, and Saltoglu (2008); Chen and Ghysels (2010); Engle, Ghysels, and Sohn (2008); Forsberg and Ghysels (2006); Ghysels, Santa-Clara, and Valkanov (2005); and León, Nave, and Rubio (2007) among others.

[5] Surveys of MIDAS regressions and related methods appear in Armesto, Engemann, and Owyang (2010); Andreou, Ghysels, and Kourtellos (2011); and Sinko, Sockin, and Ghysels (2010).

high-frequency (daily) monetary instruments. Next we combine the identified high-frequency monetary policy shocks with the low-frequency (monthly or quarterly) macroeconomic data in our MIDAS approach and make comparisons with traditional VAR models.

2.1 Dealing with data of different sampling frequency

There are at least two approaches to handling data sampled at different frequencies. One approach relies on state space models and the Kalman filter; the other relies on a regression-based approach. The former treats the low-frequency data as "*missing data*" and the Kalman filter is a convenient computational device to extract the missing data.[6] It is also worth recalling that state space models and Kalman filtering have been extensively used in the formulation of monetary policy - where the policy is viewed as a linear quadratic optimal control problem.[7] Typically, the state space models considered in this literature are very stylized and do not deal with the intricate details of high frequency data releases. Namely, the Kalman filter is not used for the purpose of handling mixed frequency data - but rather for the purpose of extracting a latent state process in a linear system monetary policy model. When state space models are applied to high (and low) frequency data they can be quite involved, as one must explicitly specify a linear dynamic model for all series involved: high-frequency data series, latent high-frequency series treated as missing, and low-frequency observed processes. The system of equations therefore typically requires numerous parameters to estimate: parameters from the measurement equation, the state dynamics and the error processes. Thus such an approach is computationally involved and more prone to specification errors compared with the regression-based approach we discuss next.

An alternative regression-based approach using so-called MIDAS regressions has emerged in recent years that allows us to estimate regression models with a combination of data sampled at different frequencies. It is a regression framework that is parsimonious (notably not requiring the modeling of the dynamics of each daily predictor series) in contrast to the Kalman-filter approach.

The regression-based approach we pursue can be viewed as part of a VAR system, albeit one that consists of data sampled at different frequencies. The mixed frequency data VAR is not parsimoniously parameterized. We will therefore select the key equation of interest from the mixed frequency VAR and estimate it with a frugal, yet flexible, parametric approach involving both high and low frequency data. Giving up the completely specified mixed frequency VAR will entail some compromises with regards to the identification of monetary policy shocks. We will take an agnostic approach to the identification of monetary shocks - notably via the analysis of various shock specifications.

We start with the VAR for mixed frequency data introduced in Ghysels (2011). Our goal here is not to be general, but rather provide a tailored example suitable to understand the source and structure

[6] See for example, Harvey and Pierse (1984); Harvey (1989); Zadrozny (1990); Bernanke, Gertler, and Watson (1997); Mariano and Murasawa (2003); Mittnik and Zadrozny (2004); Aruoba, Diebold, and Scotti (2009); Bai, Ghysels, and Wright (2009); and Kuzin, Marcellino, and Schumacher (2009); among others. A recent wave of applications revolve around nowcasting. A number of recent papers also document the gains of real-time forecast updating, sometimes also incorporating nowcasting when it is relevant to current-quarter assessments. See for instance, Doz, Giannone, and Reichlin (2008); Doz, Giannone, and Reichlin (2006); Stock (2006); Angelini, Camba-Mendez, Giannone, Rünstler, and Reichlin (2008); Giannone, Reichlin, and Small (2008); and Moench, Ng, and Potter (2009) among others which all use Kalman filter-based methods. A thorough analysis of gains using MIDAS regression-based methods (discussed below) appears in Andreou, Ghysels, and Kourtellos (2009).

[7] See for example, Kareken, Muench, and Wallace (1973), LeRoy and Waud (1977), among many others.

of the MIDAS regression approach we will use. In particular, we focus on monthly macroeconomic series and study how they respond to daily monetary policy shocks. Namely, we consider monetary policy shocks that occur at a daily frequency and then analyze the long-term impacts of daily monetary shocks on monthly macroeconomic data. By longer-term impact, we mean multiple month (up to two-year) horizons. To be specific, consider a stylized example involving a monthly macro series, Y_t^M, and a monthly financial series, X_t^M, also available at a daily frequency, X_{it}^D, where i denotes the day of month t (assuming there are $m = N_D$ such days in a month). In the case of a single daily and monthly series such a mixed frequency VAR can be written as a $m + 1$ dimensional system:

$$\begin{bmatrix} X_{1t}^D \\ \vdots \\ X_{mt}^D \\ Y_t^M \end{bmatrix} = \begin{bmatrix} A_0^1 \\ \vdots \\ \vdots \\ A_0^{m+1} \end{bmatrix} + \sum_{j=1}^{P} A_j \begin{bmatrix} X_{1(t-j)}^D \\ \vdots \\ X_{m(t-j)}^D \\ Y_{t-j}^M \end{bmatrix} + \begin{bmatrix} \varepsilon_t^1 \\ \vdots \\ \vdots \\ \varepsilon_t^{m+1} \end{bmatrix} \tag{1}$$

Hence, every month t we stack the daily observations together with Y_t^M into a vector sampled monthly with VAR dynamics. The last equation in the VAR system then reads as follows:

$$\begin{aligned} Y_t^M &= A_0^{m+1} + \sum_{j=1}^{P} A_j^{m+1,m+1} Y_{t-j}^M + \sum_{j=1}^{P}\sum_{k=1}^{m} A_j^{m+1,k} X_{k(t-j)}^D + \varepsilon_t^{m+1} \\ &= E[Y_t^M | I_{m,t-1}^D] \end{aligned} \tag{2}$$

where the superscripts on the A matrices indicate the row-column position. The above equation is an ADL MIDAS (or autoregressive distributed lag mixed data sampling) regression model discussed in Andreou, Ghysels, and Kourtellos (2010). Note that in the second equation, we use the more compact notation of $E[Y_t^M|I_{m,t-1}^D]$ to indicate that we look at the prediction of Y_t^M given information set $I_{m,t-1}^D$, which is the last day (m^{th}) day of month $t-1$. The superscript D indicates that we have daily (as well as past monthly) information. There are, for the above single equation, various parsimonious parameterizations suggested for such regressions that will be discussed later (see also Ghysels, Sinko, and Valkanov (2007) and Andreou, Ghysels, and Kourtellos (2010)). Note that the aforementioned VAR model also contains, besides the MIDAS regression, the impact of monthly onto future daily series and vice versa.

We are not necessarily interested in just looking at events at the end of each month. Indeed, for the purpose of policy impact analysis we would like to think of shocks that happen any time during the month. The mixed frequency VAR also allows us to examine what happens throughout the month as the flow of daily data evolves through time. Namely, the daily flow of events allow us to update predictions of the low frequency (monthly series) as well as future daily series (the latter being of less concern to us here). To do so, we introduce the following matrices, $\mathcal{N}_{[i]}$, $i = 1, \ldots, m-1$, such that:

$$\mathcal{N}_{[i]} = \begin{bmatrix} I & 0 & \cdots & \cdots & 0 & 0 \\ \mathcal{N}_{[i]}^{2,1} & I & 0 & \cdots & 0 & 0 \\ \vdots & & & & \vdots & \vdots \\ \mathcal{N}_{[i]}^{i+1,1} & \cdots & \mathcal{N}_{[i]}^{i+1,i} & I & \vdots & 0 \\ \vdots & & \vdots & 0 & \ddots & \vdots \\ \mathcal{N}_{[i]}^{m+1,1} & \cdots & \mathcal{N}_{[i]}^{m+1,i} & 0 & \cdots & I \end{bmatrix} \tag{3}$$

where all $\mathcal{N}_{[i]}^{\cdot,\cdot}$ are scalars. Then the mixed frequency VAR can be characterized by:

$$\mathcal{N}_{[i]} \begin{bmatrix} X_{1t}^D \\ \vdots \\ X_{mt}^D \\ Y_t^M \end{bmatrix} = A_0 + \sum_{j=1}^{P} A_j \begin{bmatrix} X_{1(t-j)}^D \\ \vdots \\ X_{m(t-j)}^D \\ Y_{t-j}^M \end{bmatrix} + \varepsilon_t \tag{4}$$

To clarify the role played by the transformation appearing in (3), let us for instance take a look at $\mathcal{N}_{[1]}$, which applies to a first daily data becoming available in the month:

$$\mathcal{N}_{[1]} = \begin{bmatrix} I & 0 & \cdots & 0 \\ \mathcal{N}_{[1]}^{2,1} & I & \cdots & 0 \\ \vdots & 0 & \ddots & \vdots \\ \mathcal{N}_{[1]}^{m+1,1} & 0 & \cdots & I \end{bmatrix}$$

Then the last equation in the system reads:

$$\begin{aligned} Y_t^M &= A_0^{m+1,1} - \mathcal{N}_{[1]}^{m+1,1} \underbrace{X_{1t}^D}_{\text{New Info}} + \sum_{j=1}^{P} A_j^{m+1,m+1} Y_{t-j}^M \\ &\quad + \sum_{j=1}^{P} \sum_{k=1}^{m} A_j^{m+1,k} X_{k(t-j)}^D + \varepsilon_t^{m+1,1} \\ &= E[Y_t^M | I_{1,t}^D] \end{aligned} \tag{5}$$

which is the ADL MIDAS regression model with (one) lead(s) - hence the information set $I_{1,t}^D$ - discussed in Andreou, Ghysels, and Kourtellos (2010). The new information can also be written in terms of a VAR innovation, namely:

$$\begin{aligned} Y_t^M &= A_0^{m+1,1} - \mathcal{N}_{[1]}^{m+1,1} A_0^1 - \mathcal{N}_{[1]}^{m+1,1} \varepsilon_t^1 \\ &\quad + \sum_{j=1}^{P} (A_j^{m+1,m+1} - \mathcal{N}_{[1]}^{m+1,1} A_j^{1,1}) Y_{t-j}^M \\ &\quad + \sum_{j=1}^{P} \sum_{k=1}^{m} (A_j^{m+1,k} - \mathcal{N}_{[1]}^{m+1,1} A_j^{1,k}) X_{k(t-j)}^D + \varepsilon_t^{m+1,1} \end{aligned} \tag{6}$$

The latter representation is in terms of the information innovation which equals ε_t^1, to the equation and re-weights all the old information accordingly.

The above mixed frequency VAR model motivates the approach in the current paper. We know that VAR models typically suffer from parameter proliferation. Mixed frequency VAR models of the type discussed above, suffer even to a greater extend of the same problem due to the stacking of daily series. Instead of analyzing the full system, we will focus on single equations - the last equation in the above VAR models that covers the monthly predictions with both past monthly and daily data - as well as potentially within month updates as in equation (5). The model specifications for the single regressions will be motivated by parsimony as well. The single equation approach has advantages, but it also has disadvantages, in particular, with respect to the identification of shocks. All innovations in the mixed frequency VAR model are determined in terms of the entire system, as particularly made clear in equation (6). In the general setting of Ghysels (2011), this may involve a combination of many high frequency (in this case daily) and low frequency series. In the single regression setting, we don't have this system identification of shocks. To deal with this issue, we will conduct various robustness exercises with respect to the characterization of what we call monetary policy shocks. For the moment, we will proceed without being specific about the sources of the shocks.

We will also simplify the notation in the regressions by dropping the explicit reference to the coefficients of the mixed frequency VAR. The MIDAS regression format also allows us to formulate multiple period forecasts directly instead of iterating through one-step ahead forecasts, namely we can write for horizon $h : E[Y^M_{t+h}|I^D_{1,t}]$, as a regression problem.[8]

2.2 Monetary Policy Shocks

We can now adopt the stylized setting to monetary policy shocks tied to FOMC meetings which may occur any time. For simplicity we assume there is an FOMC meeting the k^{th} day of month t, called day k_F. In the estimation we allow, of course, k_F to differ on a monthly basis according to the event calendar. All information available to economic agents on the days prior to an FOMC meeting will be denoted $I^{D-}_{k_F,t}$. The superscript D indicates that agents have daily information; the minus sign indicates information in question is available the day prior to day k_F of month t. We measure the impact of an FOMC meeting policy shock, $\varepsilon^D_{X,k_F,t}$, on future Y^M_{t+h} as follows:

$$Y^M_{t+h} = \tilde{\alpha}^h + \tilde{\alpha}^h_F \varepsilon^D_{X,k_F,t} + E[Y^M_{t+h}|I^{D-}_{k_F,t}]. \tag{7}$$

We interpret $\varepsilon^D_{X,k_F,t}$ as our monetary policy innovation (this shock centers around FOMC meetings). All changes outside FOMC meetings are considered noise. Hence, we measure the incremental impact of $\varepsilon^D_{X,k_F,t}$ on Y^M_{t+h}, after controlling for the expectation of the latter given information prior to the FOMC meeting, expressed via $E[Y^M_{t+h}|I^{D-}_{k_F,t}]$. The contributions of the paper pertain to how we specify *(i)* the monetary policy shock and *(ii)* expectations, $E[Y^M_{t+h}|I^{D-}_{k_F,t}]$.

A monetary policy shock is identified in equation (7) via *(i)* the timing of FOMC meetings and *(ii)* the choice of relevant financial time series $\varepsilon^D_{X,k_F,t}$. Incorporating the timing of FOMC meetings to identify monetary policy shocks has been used in a number of recent papers, notably Cochrane and Piazzesi (2002) and Faust, Swanson, and Wright (2004). Cochrane and Piazzesi use interest rates to define monetary shocks by regressing changes in the federal funds rate target on interest rates just before each change is made. FSW use fed funds futures contracts to measure the effect of a policy surprise on the expected trajectory of interest rates.

In our approach, we also use the timing of monetary policy shocks, but we rely on entirely different tools than the existing literature to understand the impact of those shocks on macroeconomic variables. What sets our approach apart is that we use a novel data-driven method to measure the long-term impact of daily monetary policy shocks. In principle, we could construct the shocks from very complicated

[8] In the forecasting literature one makes a distinction between iterated and direct forecasting see e.g. Marcellino, Stock, and Watson (2006).

multivariate models or from narrative evidence. The mixed frequency VAR model discussed in the previous subsection provided such an example. We could identify monetary policy shocks in the full system, but we prefer not. Hence, we will identify shocks via simpler models, but doing it for a number of shock specifications in order to robustify our findings.

For illustrative purposes, we use a simple statistical framework. Namely, suppose that we have a *daily* AR(p^D) model for the monetary instrument $X^D_{i,t}$; then, for p^D = 1, we have

$$X^D_{i,t} = c_0 + c_1 X^D_{i-1,t} + \varepsilon^D_{X,i,t}. \tag{8}$$

For discussion, consider the random walk case with c_0 = 0 and c_1 = 1. In all the subsequent analysis it is easy to replace the above equation with alternative shock specifications, something that will be done later. Where we start to differ from the existing literature is in how we handle the combination of daily data and monthly or quarterly macroeconomic data. Cochrane and Piazzesi (2002) study monetary policy shocks defined as movements in the federal funds rate target relative to daily interest rate data. Specifically, they measure the unexpected target rate change in monetary policy as the change in the one-month eurodollar rate up to two days prior to a change in the federal funds rate target. To identify monthly monetary policy shocks, Cochrane and Piazzesi *aggregate* their daily monetary policy shock series which they then compare to the CEE monthly monetary policy shock series.

Aggregation of the shocks raises timing issues that are not well accounted for. Hamilton (2008a) draws attention to this and finds that the timing of changes in expectations can indeed be important. In estimating the impact of the futures market on the one-year Treasury yield rate, he finds that changes in the fed funds futures rate have a larger effect around the middle rather than the beginning or end of the month.[9] Hamilton went on to conclude that the "*model captures a clear tendency in data for the impact to vary across the month"*. Because macroeconomic data are typically monthly, taking timing into consideration can be problematic. Hamilton, for example, estimates daily effects by adding a series of calendar dummies.

In a related paper, Hamilton (2008b) examines the effects of long-term mortgage rates on home sales. He also quantifies the effects of monetary policy surprises (measured using fed funds futures) on mortgage rates and homes sales. In the specification closest to our approach, Hamilton examines the effects of daily changes in the fed fund futures rate on the monthly value of home sales. To combine data of different frequencies Hamilton employs a MIDAS-like regression in which he weights daily fed funds futures data with a Weibull distribution function. The Weibull distribution is assumed to capture the varying lengths of time that heterogenous agents spend looking for houses.

There are some clear differences between our work and that of Hamilton (2008b). First, in his paper monetary policy effects only work through the housing market while we expand the number of channels through which monetary policy can affect the macro economy. Second, in his daily MIDAS-like specification Hamilton does not isolate any special effects that could arise from FOMC meetings. Therefore, every daily change in the federal funds futures rate is interpreted as a policy surprise. To be fair, Hamilton demonstrated in an earlier section of the paper that there was nothing special about Fed announcement days (which included, but were not restricted to, FOMC meeting days) when looking at the relationship between weekly innovations to mortgage rates and daily changes in the futures rate. However, Hamilton excluded all non-announcement days, while we simultaneously include both

[9] Hamilton finds that the effect of a mid-month change in the futures rate is slightly bigger than a beginning-of-the-month change and significantly greater than an end-of-the-month change.

announcement and non-announcement days in our analysis. Third, while we make explicit controls for agents' expectation of policy actions prior to FOMC meetings, Hamilton does not.

2.3 MIDAS regressions

We start with equation (2), namely a situation at the end of month $t-1$ where we want to predict month t's realization using both past monthly data and any intervening daily data. We will re-parameterize the equation and adopt what Andreou, Ghysels, and Kourtellos (2009) call a multiplicative MIDAS regression model for $E[Y_t^M | I_{m,t-1}^D]$. While this is not the most parsimonious representation, we later explain our choice. The regression is as follows:

$$\begin{aligned} Y_t^M &= a_0 + \sum_{i=1}^{L_Y} a_{iY} Y_{t-i}^M + \sum_{i=1}^{L_X} a_{iX} \varepsilon_{X,t-i}^M(\theta) + \varepsilon_{Y,t}^M, \\ \varepsilon_{X,t-i}^M(\theta) &\equiv [\sum_{j=1}^{N_D} w(j;\theta_1,\theta_2) \varepsilon_{X,j,t-i}^D], \end{aligned} \tag{9}$$

where the weights $w(j,.)$ add up to one and we assume, for simplicity, all months have the same number of trading days N_D. Note that $\varepsilon_{X,t-i}^M(\theta)$ is a monthly *parameter-driven* process and consists of weighted daily data through a MIDAS weighting scheme.[10,11] One can view the estimated weights, $w(i;\hat{\theta}_1,\hat{\theta}_2)$, as being a data-driven aggregation scheme that replaces the typically *ad hoc* aggregation used to construct same-frequency $\varepsilon_{X,t}^M$ and Y_t^M. The weighting scheme is designed to produce best linear predictions via the regression in equation (9). Note that the regression can also be written as:

$$\begin{aligned} Y_t^M &= a_0 + \sum_{i=1}^{L_Y} a_{iY} Y_{t-i}^M + \sum_{i=1}^{L_X} a_{iX} [\sum_{j=1}^{N_D} w(j;\theta_1,\theta_2) \varepsilon_{X,j,t-i}^D] + \varepsilon_{Y,t}^M, \\ &= a_0 + \sum_{i=1}^{L_Y} a_{iY} Y_{t-i}^M + \sum_{j=1}^{L_X * N_D} \tilde{w}(j;\theta_1,\theta_2,a_X) \varepsilon_{X,(j,mod(N_D),t-1-int(j/N_D)}^D + \varepsilon_{Y,t}^M, \end{aligned} \tag{10}$$

which clarifies why it is referred to as a multiplicative MIDAS regression, since $\tilde{w}(j;\theta_1,\theta_2,a_X) \equiv a_{1+int(j/N_D)X} * w((j,mod(N_D);\theta_1,\theta_2)$, with $int()$ the integer part and $mod()$ the modulo function.

[10]The weighting scheme can have any number of forms; the challenge here is to achieve flexibility while maintaining parsimony. One form of the weighting function suggested by Ghysels, Santa-Clara, and Valkanov (2004) is the Beta polynomial:

$$w(i;\theta_1,\theta_2) = \frac{f\left(\frac{k}{m},\theta_1,\theta_2\right)}{\sum_{j=1}^{m-1} f\left(\frac{j}{m},\theta_1,\theta_2\right)},$$

where

$$f(i,\theta_1,\theta_2) = \frac{i^{\theta_1-1}(1-i)^{\theta_2-1}\Gamma(\theta_1+\theta_2)}{\Gamma(\theta_1)\Gamma(\theta_2)},$$

θ_1 and θ_2 are hyper-parameters governing shape of the weighting function, and $\Gamma(\theta_p)$ is the standard Gamma function. As discussed, for instance, in Ghysels, Sinko, and Valkanov (2007), various parameterizations can obtain strictly decreasing or humped-shaped weighting functions.

[11]In the specification of the effects of monetary policy on home sales, Hamilton (2008a) uses as his measures of innovation either daily changes in the fed funds futures rates or changes in mortgage rates, assuming the latter is a martingale. Similar to our specification, Hamilton uses his monetary policy innovation measures as right-hand-side variables.

There are advantages and drawbacks to using the multiplicative MIDAS scheme. The obvious drawback is that it is less parsimonious than a single weighting scheme driven by a smaller set of parameters. The advantages are convenient for the current application. First, as noted earlier, the process $\varepsilon^M_{X,t-i}(\theta)$ can be directly compared with temporal aggregation schemes, for example, to those studies that construct monthly data from higher-frequency daily data; for example, we can compare $\varepsilon^M_{X,t-i}(\theta)$ to the monthly monetary shocks constructed by Cochrane and Piazzesi (2002). Second, the multiplicative scheme is also appealing for constructing $E[Y^M_{t+h}|I^{D-}_{k_F,t}]$ on any day of the month prior to an FOMC meeting. Indeed, so far we have only produced a linear expectation using daily data up to the end of month $t-1$.

To proceed, we need (i) within-month updates and (ii) multiple-horizon predictions to compute $E[Y^M_{t+h}|I^{D-}_{k_F,t}]$. To address both issues, we use a MIDAS regression with leads as defined in Andreou, Ghysels, and Kourtellos (2009). Specifically we consider the following regression using data up to the eve of an FOMC meeting:

$$\begin{aligned} Y^M_{t+h} \quad &= \quad a^h_0 + a^h_L \left[\sum_{j=1}^{k_F-1} \frac{1}{s(k_F-1)} w\left(n; \theta^L_{1h}, \theta^L_{2h}\right) \varepsilon^D_{X,k_F-j,t} \right] \\ &\qquad + \sum_{i=1}^{L_Y} a^h_{iY} Y^M_{t-i} + \sum_{i=1}^{L_X} a^h_{iX} [\sum_{j=1}^{N_D} w(j; \theta_{1h}, \theta_{2h}) \varepsilon^D_{X,j,t-i}] + \varepsilon^{M,h}_{Y,t}. \end{aligned} \tag{11}$$

Note that, equation (11) is different from equation (9) in two ways: (i) we added a term that reflects the intervening $k_F - 1$ days prior to the FOMC meeting in month t and (ii) we predict Y^M_{t+h} for any h not necessarily one. The latter means that all parameters – including the MIDAS weighting scheme hyper-parameters – potentially vary with h. Moreover, we note that a separate polynomial weighting scheme $w\left(n; \theta^L_{1h}, \theta^L_{2h}\right)$ applies to the within-month daily data prior to an FOMC meeting. For the sake of convenience, we impose $\theta^L_{ih} = \theta_{ih}$ for $i = 1$ and 2. This implies that we use a partial sum of the within-month weights determining $\varepsilon^M_{X,t}(\theta)$ to measure the real-time update prior to an FOMC meeting. Because we use a partial sum, the within-month weights no longer sum to one, and, therefore, we normalize the partial-sum weights by $1/(s(k_F-1))$, where $s(k_F-1)$ is the sum of the weights for the first $k_F - 1$ days. The scaling makes the slope parameter, a^h_L, in equation (11) invariant to the number of days prior to an FOMC meeting within a given month. For convenience the shape of the weighting function is preserved in the contemporaneous period because it allows us to easily estimate the models with a smaller parameter space, to avoid separate estimation of the parameters θ^L_{1h} and θ^L_{2h}.

It is also noteworthy that Andreou, Ghysels, and Kourtellos (2009) recommend against using a single series to produce real-time MIDAS regression forecasts of macroeconomic variables but instead suggest combining a large cross-section of daily financial data. They combine the MIDAS-regression predictions based on a single series to produce improved predictions that exploit the entire cross-section of financial series. While we could adopt such a strategy we instead simply use the series ε^D_X as the single predictor for future Y^M. One reason we use this simplified approach is that it facilitates comparisons with VAR models. Of course, the VAR models we consider are bivariate. To compare our approach with VAR models that use more low- or high-frequency data, one would have to augment equation (11), with either additional low- or high-frequency series. This approach would also have to add MIDAS polynomials or rely on combination schemes as in Andreou, Ghysels, and Kourtellos (2009).

Merging equations (7) and (11) yields our baseline model to compute impulse response function for the low-frequency impact of a daily monetary policy shock; namely

$$\begin{aligned} Y_{t+h}^M &= \tilde{\alpha}^h + \tilde{\alpha}_F^h \varepsilon_{X,k_F,t}^D + a_L^h \left[\sum_{j=1}^{k_F-1} \frac{1}{s(k_F-1)} w\left(n;\theta_{1h},\theta_{2h}\right) \varepsilon_{X,k_F-j,t}^D \right] \\ &\quad + \sum_{i=1}^{L_Y} a_{iY}^h Y_{t-i}^M + \sum_{i=1}^{L_X} a_{iX}^h [\sum_{j=1}^{N_D} w(j;\theta_{1h},\theta_{2h}) \varepsilon_{X,j,t-i}^D] + \varepsilon_{Y,t}^{M,h}. \end{aligned} \tag{12}$$

This equation includes the following new ingredients: (i) the parameter, $\tilde{\alpha}_F^h$, designed to measure impulse responses of daily shocks at horizon h; (ii) the proper timing of expectations via the MIDAS-with-leads term up to $k_F - 1$, the eve of the FOMC meeting; and (iii) the data-driven weights of the MIDAS polynomials instead of pre-set aggregation schemes. These three ingredients set our approach apart from the existing literature.

In the previous sections we proposed a model that exploits the differences in the frequencies of macro and financial variables to identify two kinds of monetary policy shocks. We briefly discussed how we interpret FOMC shocks; now, we provide some context for the daily innovation, $\varepsilon_{X,j,t}^D$. In particular, we discuss the difference between (i) the shock identified by structural restrictions to the monthly VAR and (ii) the sum of the daily shocks identified by (12).

Equation (12) includes three shocks: (i) the non-monetary monthly innovation, $\varepsilon_{Y,t}^M$; (ii) the daily fed funds innovation, $\varepsilon_{X,j,t-i}^D$; and (iii) the additional effect coming out of FOMC meetings, $\varepsilon_{X,k_F,t}^D$. One might ask why it is important to distinguish between (ii) and (iii). In many cases, monetary policy shocks are identified in VARs by timing restrictions – that is, the monetary shock can react contemporaneously to current changes in the macro variables but not vice versa. These types of restrictions could prove invalid, however, if the macro variables in question are expectations variables that may indeed be influenced contemporaneously by monetary policy (or at least the expected path of policy).[12] For these variables news is important because it might provide information about the (systematic) component of monetary policy. Thus, in monthly models, identifying the difference between exogenous changes in the path of monetary policy and the effect of news about another variable that policy might react to is virtually impossible.

2.4 The VAR Model and High-Frequency Policy Shocks

We return now to VAR models involving low frequency data only. For illustration, the analysis in this subsection assumes that $X_{i,t}^D$ is white noise without drift. We make this simplification because it streamlines the presentation without loss of generality. We use as our motivating example a bivariate VAR(1) model involving a monthly macro series Y_t^M and a monthly financial series X_t^M. Then, the VAR(1) can be written as follows:

$$\begin{aligned} Y_t^M &= a_{01}^M + a_{11} Y_{t-1}^M + a_{12} X_{t-1}^M + \varepsilon_{Y,t}, \\ X_t^M &= a_{02} + a_{21} Y_{t-1}^M + a_{22} X_{t-1}^M + \varepsilon_{X,t}, \end{aligned} \tag{13}$$

[12] FSW found that the common assumption restricting prices to not respond contemporaneously to monetary policy is erroneous. That is, when this restriction is imposed on the data they are unable to find any solution to their model.

where we assume – also for simplicity – the following aggregation scheme for daily data:

$$X_t^M = \sum_{i=1}^{N_D} \frac{1}{N_D} X_{i,t}^D.$$

For the moment, we focus on the top equation in (13). Since daily data are available, we might consider a linear projection of Y_t^M onto daily M lags X_{it}^D which would result in this equation:

$$Y_t^M = \tilde{\alpha}_{01} + \tilde{a}_{11} Y_{t-1}^M + \tilde{a}_{12} \sum_{i=1}^{M} w_i L_D^i X_{i,t-1}^D + \tilde{\varepsilon}_{Y,t}^M, \tag{14}$$

where L_D is a daily lag operator and we express the linear projection as of a slope coefficient $\tilde{a}_{12}$ times individual weights w_i.[13] To compare equation (14) with equation (13) we must take into account the aggregation scheme:

$$Y_t^M = \tilde{\alpha}_{01} + \tilde{a}_{11} Y_{t-1}^M + \tilde{a}_{12} X_{t-1}^M + \tilde{a}_{12} \sum_{i=1}^{N_D} (w_i - \frac{1}{N_D}) L_D^i X_{i,t-1}^D + \tilde{\varepsilon}_{Y,t}^M. \tag{15}$$

Note that the aggregation scheme in equation (13) amounts to using the "wrong" weights when compared with the weights used in equation (14) - the linear projection using daily data. Specifically, equation (13) has: (i) an omitted regressor $\tilde{a}_{12} \sum_{i=1}^{N_D} (w_i - 1/N_D) L_D^i X_{i,t-1}^D$, and (ii) its slope coefficient for X_{t-1}^M may potentially differ ($\tilde{a}_{12}$ and a_{12} are typically not identical). The econometric implications of omitted regressors – in terms of biases and asymptotic inefficiencies in estimation – are discussed at length in Andreou, Ghysels, and Kourtellos (2010).[14] Note also that, due to the omitted regression mis-specification and bias, some of the daily impact appears in the residuals of the VAR; this means that the interpretation of policy shocks is affected in a non-trivial manner.

3 Empirical Results

We start with a description of the data in subsection 3.1, then cover the empirical results in subsection 3.2. Subsection 3.3 examines the impulse response functions.

3.1 Data

Consistent with much of the literature on monetary policy shocks, our monetary policy instrument is the federal funds rate; the substantive difference of our paper is that we consider daily federal funds rate data. These data are taken from the Federal Reserve Board and the sample period is January 1, 1960 to July 31, 2009. We test the model with a variety of macroeconomic data. Each variable is estimated separately in the bivariate framework proposed in the previous section. The sample period used for

[13] By analogy, we will later use L_M for the monthly lag operator.

[14] The decomposition in equation (10) and that discussed in Andreou, Ghysels, and Kourtellos (2010) are slightly different; namely, the latter takes into account that the w_i's add up to one which leads to a decomposition that is more accurate yet more involved. Technically, not restricting the w_i's to sum to one does not impact the econometric implications discussed here.

each regression depends on the availability of the given macroeconomic data. Table 1 summarizes the data and its sources. Figure 1 plots each of the monthly series starting in 1960.

Our macroeconomic variables are those commonly found in the monetary VAR literature, e.g., industrial production, prices, and employment. The price measures are core CPI and all-items (or headline) CPI. Our employment measure is total-nonfarm payroll employment. In addition we also study the effect of monetary policy on these variables: retail sales, consumer sentiment, inflation expectations, the composite index of coincident indicators, the composite index of the 10 leading indicators, real personal income, consumer credit outstanding plus banking credit of all commercial banks, and the unemployment rate. All monthly variables are seasonally-adjusted and log-differenced, except for inflation expectations and unemployment which are in rates.

3.2 Results

Table 2 presents the results from the two-stage monetary policy regressions for the macroeconomic variables in Table 1. Column 1 presents the results from a regression that includes a dummy to indicate an FOMC meeting. In this regression, we restrict the MIDAS parameters to 1 and omit the term representing the effect of days between the start of the month and the FOMC meeting, which essentially creates a standard ordinary least squares (henceforth, OLS) regression in the VAR that has the additional FOMC dummy. We find evidence of a persistent price puzzle for core inflation but no effect of the FOMC dummy – identified by the statistically insignificant coefficient, $\widetilde{\alpha}_F$ – on headline inflation.[15] The FOMC dummy has a positive effect on the coincident composite index but the opposite effect on the leading composite index. We find, perhaps counterintuitively, that tightening monetary policy (increasing the interest rate) causes real personal income, industrial production, and employment to increase. Additionally, the coefficient on the unemployment rate is negative and statistically significant, meaning tightening monetary policy causes unemployment to fall. Finally, the FOMC dummy has a positive effect on consumer credit – given that consumer credit measures credit outstanding it seems likely that individuals close accounts when interest rates rise. These results suggest that the regressions reported in column 1 are plagued by specification errors.[16]

Columns 2 and 3 represent the estimation of equation (11) without restrictions on the MIDAS hyper-parameters, θ_1 and θ_2. Estimation for column 2 suppresses the effects of days between the start of the month and the day of an FOMC meeting; however, these days are included in the estimation for column 3.

[15] Previous work has shown that the price puzzle may be explained by un-modeled expectations that have temporary effects on inflation (see Hanson (2004) and Francis and Owyang (2005)) suggesting that accounting for the timing of events helps mitigate the exclusion of expectations from the model. Barth and Ramey (2001) provide an alternate explanation for the *price puzzle*. It goes: for firms that rely on borrowing working capital to pay workers and having to pay said workers before sales revenues are realized an increase in interest rates represents an increase in costs to these firms (i.e., increases in the price of loans). The increase in costs shifts goods supply curves inward while lowering prices. Thus, once the supply side is modeled, an increase in the price level is a direct consequence of contractionary monetary policy.

[16] Of course this depends on whether one believes these monetary models are correct. As a further exercise, we reran our OLS regressions replacing our FOMC shock with that of Romer and Romer, restricting the sample period to 1969:01 - 1996:12, the overlap of the two datasets. Overall, the shocks from (8) and from Romer and Romer deliver similar conclusions in standard VAR framework. This suggests that differences between our results and those in Romer and Romer (2004) result from the differences in the timing of the MIDAS regressions and the standard monthly VAR rather than the specification of the shock.

The results in column 2 show that estimating the macroeconomic variables' (real variables') equations with weighted daily data yields results slightly different from the OLS results. For example, we find that an increase in the fed funds rate has no effect on real variables. Moreover, when accounting for the timing of the monetary shock using the MIDAS regression, the price puzzle disappears; the coefficient on core inflation is still positive but becomes statistically negligible.

Interestingly, when we include the intervening days leading up to an FOMC meeting, we find that both unemployment and consumer sentiment have statistically significant coefficients - unemployment is positive and consumer sentiment is negative. This finding suggests that, for example in anticipation of higher interest rates, firms reduce their workforce and consumers lose optimism about the state of the economy. However, on the day of the FOMC meeting, when interest rates actually rise, there is a significant increase in consumer sentiment. The opposite interpretation would prevail in anticipation of a fall in interest rate.

Figure 2 displays the estimated MIDAS weights for select variables. The leading index (CI-leading), CPI core, and consumer credit correspond to the bold-faced (i.e. the MIDAS coefficients that are statistically significant at the 10 percent level of significance) entries in Table 2. Note that the MIDAS hyper-parameters are tested against the null of 1, which corresponds to equal weights used by OLS. Superimposed on the estimated MIDAS weights are the equal weights that are actually used in the OLS regressions (horizontal line) in column one of Table 2. A common theme for the MIDAS hyper-parameters, θ_i, $i = 1, 2$, is that variables that are viewed as "expectations-influenced", e.g., the leading indicators, place greater weight on more-recent data. Variables that can respond quickly, e.g., consumer credit outstanding, also place more weight on more-recent data. On the other hand, variables needing more time to adjust to more-recent data, e.g., inflation, place a little more weight on later-in-the-month data. Keeping in mind that these differences are measured in days, these results suggest that the timing of the innovations to the funds rate – when during the month – may alter the effect of the innovations. In all cases, the results also suggest that a simple monthly average of the daily data may be misleading.

The results in Figure 2 clearly illustrate why the aggregation scheme in the original VAR amounts to using the wrong weights. As noted before, a consequence - in addition to the loss of information regarding the policy shock - is an omitted regressor which potentially biases the estimates of the impact of monetary policy shocks. The empirical results suggest that these potential biases are indeed real and important and affect the empirical specification of monetary policy shocks. We strengthen this finding by comparing impulse response functions obtained from VAR and MIDAS regressions.

3.3 Impulse Response Functions

To generate impulse responses, we project futures values of the monthly variables onto the daily $(t-1)$ data. That is, we project each of Y^M_{t+h}, $h = 0, \ldots, 24$ onto the right-hand side of equation (12). This is similar to the local-projection approach taken by Jordà (2005). Note also that we have omitted the intervening days as they are relevant only for the current-period model. We interpret the coefficient on the FOMC dummy at each horizon, h, as the impulse response of the macroeconomic variable to a monetary policy shock – the monetary surprise originating on a typical FOMC meeting day. The impact effects $h = 0$ are the results presented in Table 2 discussed above. Confidence intervals for our impulse responses are calculated as $\pm 1.65*$ *standard errors* of the FOMC dummies.

Figure 3 plots the impulse responses to a one-unit increase in the FOMC dummy from the MIDAS regressions. For the most part, monetary policy surprises have no statistically significant effect on the selected macroeconomic variables. That is, the majority of the impulse responses are statistically indistinguishable from zero. However, there are a few exceptions. After an insignificant initial response, inflation expectations respond positively and significantly after three months and remain significant two years hence – it seems individuals anticipate a reversal of policy which would eventually lead to higher prices. Between 3 to 15 months, there is a significant increase in consumer credit available. After 21 months, we also see a significant fall in core inflation. Although, core inflation actually fell after five months it only became significant in the later part of the response period.

We compare our MIDAS impact-point responses to contractionary monetary policy shocks to counterpart responses presented elsewhere in the literature. In the CEE and Romer and Romer (2004) benchmark specifications, inflation rises in response to tightening monetary policy.[17] However, unlike CEE, we find that our measure of output (industrial production) rises in response to the same shock. Romer and Romer (2004) also find that industrial production rises for the first 6 months after contractionary monetary policy shock thereafter becoming negative for the remainder of the response period. Similar to Cochrane and Piazzesi (2002), when there is an unanticipated increase in the federal funds rate, we find increases in employment and inflation. Using futures data to capture monetary policy, FSW find that both output and prices initially fall in response to a contractionary monetary policy shock (no price puzzle) which is the opposite of what we found. Finally, like us, Christiano, Eichenbaum, and Evans (1996) find that retail sales fall in response to a contractionary monetary policy shock but unlike us also find that employment falls and unemployment rises.

To further evaluate the differences between the results VAR and MIDAS regression-based impulse responses, we turn our attention to Figure 4 which superimposes the OLS point response estimates onto the impulse responses generated by MIDAS. The figure shows that the OLS (VAR) point responses for the composite index (leading), the core CPI, and to a lesser extent consumer credit, industrial production, and employment all lie outside the range predicted by their MIDAS counterparts. When we do the reverse and superimpose the impulse responses from MIDAS onto the OLS responses (Figure 5), we obtain the same predictions namely, the composite index (leading), core CPI, consumer credit, industrial production, and employment all lie outside the confidence sets of their MIDAS counterparts but now the composite index (coincident), unemployment, and consumer sentiment do as well.

4 Robustness Checks

In this section we calculate impulse responses using different estimates of monetary policy shocks. One drawback of using daily federal funds interest rate to identify innovations to monetary policy is the unavailability of daily data on price and real economic activity with which to estimate the policy-makers's reaction function. However, as in traditional monetary VARs we only have one observation per month of the shock: this is a normalization we impose in the estimation. In the monetary policy literature there are numerous measures of monthly monetary shocks that account for output and price movements. We use two such measures from the literature as robustness checks of against the results from our MIDAS approach with a simple autoregressive walk monetary shocks (henceforth AR). The

[17]The inflation rise in Romer and Romer (2004) is greater using the CPI than the PPI. The latter response, while positive, is extremely close to zero. After a year the price responses are negative, and remains so for the duration of the response period.

candidate monetary policy innovations are:

1. **OLS Shock**: obtained by running the monthly federal funds rates on 13 lags of itself, industrial production and inflation.

2. **Romer and Romer (2004) Shock**: Romer and Romer (2004) devise a measure of monetary policy that purges changes in the fed funds rate around FOMC meetings of their *endogenous* and *anticipatory* components.[18] Similar to the AR shock, the Romers' shock is timed to occur on the day of the FOMC meeting. Their shock incorporates the information gleaned from minutes of the FOMC meetings to construct the target funds rate and the Greenbook forecasts of output, unemployment, and inflation. With this, Romer and Romer extract changes which occur from anticipated future changes in the economy.[19]

We obtain three sets of impulse responses, one for each of the monetary policy shocks; *AR*, *OLS*, and *Romer and Romer*. Figure 6 plots the three shocks over the sample period 1969:01 - 1996:12. The sample coverage is exactly that of Romer and Romer (2004). The pairwise correlations for three innovations are as follows: $corr(OLS, ROMER) = 0.44$, $corr(OLS, AR) = 0.11$, $corr(AR, ROMER) = 0.03$. These pairwise correlations are relatively low. Additionally, the OLS shock is the most volatile, especially during the period covering the late 1970's to mid 1980's.

Using these disparate shocks to evaluate the impact of monetary policy surprise should highlight any potential shortcoming of using the simple AR(p) process to identify monetary policy shock. Failure to find significant differences in the impulse responses to the various shocks will indicate that the differences between our benchmark MIDAS results and those of the VAR literature are mainly due to differences in the propagation mechanisms from the estimation strategy and not due to differences in the identification of the shock. Figure 7 plots the impulse responses using MIDAS technique for each of the three *assumed-exogenous* monetary policy shocks. That is, we calculate the impulse responses as described earlier but do so for each of the above-mentioned shocks, holding all other right hand side variables intact. Therefore, for each figure the only difference in obtaining the impulse response is the measure of the exogenous innovation $\varepsilon^D_{X,k_F,t}$ on the right hand side of the MIDAS regression. With a few exceptions, there are little differences between the respective impulse responses. Qualitative differences arise in the reponses of the leading composite index, retail sales, consumer sentiment, core inflation and real personal income. The leading composite index, retail sales and consumer while positive for the *Romer and Romer* and *AR* shocks are negative for the *OLS* shock. However, consumer sentiment is closer to zero for OLS as it mainly fluctuates around the *x*-axis. Core inflation and real personal income are predominantly negative for the AR shock but positive for the OLS and Romer and Romer shocks. While there are differences in the point estimates the error bands appear to be wide enough to render these differences insignificant.

5 Conclusions

We proposed using MIDAS regressions - regression models designed to accommodate data sampled at different frequencies and therefore accurately capture the daily timing of innovations to monetary

[18] A similar approach was taken by Froyen and Waud (2002).

[19] The FOMC currently releases the target for the fed funds rate. Prior to 1994, however, the target was not released.

policy instruments to determine the low frequency macroeconomic effects of high frequency policy changes. We find that taking into account the timing of the shocks is important and can alleviate some of the puzzles in standard monthly VARs (e.g., the price puzzle). We find that policy shocks are most important to variables thought of as being heavily expectations oriented and that, contrary to some VAR studies, the effects of FOMC shocks on real variables are small. Our approach solves the tension that exists between the low-frequency phenomenon of policy impact we want to measure and the availability of high-frequency (daily) data on monetary policy surprises. The approach we propose can be applied to many other settings as well.

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Table 1: Data Series and Sources

Series	Source	Sample Period	
Monthly Data			
Coincident Index	The Conference Board	1960:01-2009:07	Log Diff
Leading Index	The Conference Board	1960:01-2009:07	Log Diff
CPI: All Items	Bureau of Labor Statistics	1960:01-2009:07	Log Diff
CPI: Core	Bureau of Labor Statistics	1960:01-2009:07	Log Diff
Real Personal Income	Bureau of Econ. Analysis	1960:01-2009:07	Log Diff
Consumer Credit	Federal Reserve Board	1960:01-2009:07	Log Diff
Inflation Expectations	Univ of Michigan Survey	1983:01-2009:07	Rates
Industrial Production	Federal Reserve Board	1960:01-2009:07	Log Diff
Consumer Sentiment	Univ of Michigan Survey	1978:01-2009:07	Log Diff
Payroll Employment	Bureau of Labor Statistics	1960:01-2009:07	Log Diff
Unemployment	Bureau of Labor Statistics	1960:01-2009:07	Rates
Retail Sales	Census Bureau	1967:01-2009:07	Log Diff
Daily Data			
Eff. Fed Funds Rate	Federal Reserve Board	1/1/60 - 7/31/09	n/a

Table 2: Empirical Parameter Estimates for h = 0

The columns report the following: (1) is a standard OLS regression with the FOMC dummy. (2) is the MIDAS regression with the FOMC dummy but excluding the effect of days in the current month. (3) is the MIDAS regression with the FOMC dummy and days in the current month. Boldfaced entries indicates significant at the 10 percent level using robust standard errors. The MIDAS hyper-parameters are against the null of 1, whereas the OLS coefficients are against the null hypothesis of zero.

Parameter	Composite Index: Coincident			Composite Index: Leading			CPI: Headline		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\widetilde{\alpha}$	**0.060**	**0.055**	0.056	**0.051**	0.028	0.027	**0.086**	**0.088**	**0.088**
a_{1Y}	**0.230**	**0.262**	**0.267**	**0.206**	**0.261**	**0.261**	**0.478**	**0.483**	**0.483**
a_{2Y}	**0.209**	**0.211**	**0.215**	**0.222**	**0.218**	**0.223**	0.058	0.056	0.059
a_{3Y}	**0.155**	**0.131**	0.138	**0.168**	**0.133**	**0.133**	0.033	0.039	0.042
a_{4Y}	**0.099**	**0.088**	0.083	**0.164**	**0.114**	**0.115**	**0.179**	**0.172**	0.171
$\widetilde{\alpha}_F$	**0.073**	−0.012	−0.005	**−0.091**	−0.008	0.023	0.022	0.031	0.028
θ_1		0.980	0.981		**2.436**	**2.452**		1.481	1.544
θ_2		1.736	1.908		**3.120**	**3.078**		1.230	1.318
a_{1X}	−0.003	−0.102	−0.126	**−0.323**	**−2.759**	**−2.624**	**0.055**	**0.734**	0.708
a_{2X}	−0.004	−0.117	−0.179	**−0.245**	**−4.035**	**−4.060**	**0.050**	**0.461**	0.493
a_{3X}	0.008	0.224	0.221	−0.013	−0.615	−0.549	−0.007	**0.520**	0.513
a_{4X}	**−0.066**	−0.512	−0.510	−0.056	**1.311**	1.222	0.013	0.065	0.014
a_L			−0.012			−0.005			−0.062
R^2	0.31	0.31	0.31	0.39	0.34	0.34	0.45	0.45	0.45

Parameter	CPI: Core			Real Personal Income			Consumer Credit		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\widetilde{\alpha}$	**0.046**	**0.050**	0.052	**0.279**	**0.271**	**0.270**	**0.088**	**0.083**	0.082
a_{1Y}	**0.197**	**0.245**	0.247	**−0.092**	**−0.080**	−0.076	**0.290**	**0.299**	**0.297**
a_{2Y}	**0.304**	**0.293**	**0.295**	0.020	0.028	0.040	**0.278**	**0.274**	**0.276**
a_{3Y}	**0.207**	**0.188**	0.180	−0.043	−0.031	−0.023	**0.161**	**0.160**	**0.162**
a_{4Y}	**0.157**	**0.128**	0.133	**0.086**	**0.080**	0.089	**0.125**	**0.132**	0.131
$\widetilde{\alpha}_F$	**0.067**	0.011	0.007	**0.098**	0.003	−0.023	**0.051**	0.042	0.038
θ_1		**3.502**	3.798		1.091	4.970		**1.762**	1.756
θ_2		**1.960**	2.133		1.032	35.860		**2.288**	2.340
a_{1X}	0.015	**1.046**	1.057	0.009	0.638	−0.035	0.027	**1.046**	1.018
a_{2X}	**0.073**	0.046	0.041	0.032	0.489	−0.049	**−0.055**	**−0.867**	−0.867
a_{3X}	0.001	**0.627**	0.621	**0.078**	**1.477**	0.384	−0.003	−0.356	−0.402
a_{4X}	**−0.023**	−0.085	−0.099	−0.047	0.091	0.015	0.031	−0.055	−0.085
a_L			−0.059			−0.043			0.039
R^2	0.60	0.60	0.59	0.04	0.04	0.04	0.54	0.54	0.54

Table 2 continued

Parameter	Inflation Expectations			Industrial Production			Consumer Sentiment		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\widetilde{\alpha}$	**0.225**	**0.229**	0.237	**0.093**	**0.090**	**0.100**	−0.100	**−0.700**	**−0.719**
a_{1Y}	**0.755**	**0.787**	**0.757**	**0.178**	**0.186**	**0.212**	0.001	−0.051	**−0.052**
a_{2Y}	**−0.125**	**−0.131**	−0.101	**0.118**	**0.118**	**0.131**	−0.056	−0.069	**−0.069**
a_{3Y}	**0.219**	**0.210**	0.210	**0.169**	**0.158**	**0.170**	−0.069	−0.080	**−0.079**
a_{4Y}	−0.051	−0.071	−0.078	**0.114**	**0.095**	**0.074**	−0.013	0.003	0.003
$\widetilde{\alpha}_F$	0.047	0.036	0.066	**0.273**	0.108	0.075	0.609	1.333	**1.215**
θ_1		**14.572**	38.359		1.370	**30.641**		**2.990**	**3.014**
θ_2		**12.496**	12.115		1.003	**20.779**		**13.042**	**12.530**
a_{1X}	0.051	**0.573**	−0.504	−0.016	**2.393**	**0.728**	**−1.544**	**−9.298**	**−10.528**
a_{2X}	0.036	**0.8485**	−0.475	0.034	0.430	−0.190	0.176	**−4.833**	**−5.094**
a_{3X}	−0.051	**−0.714**	0.486	−0.065	−0.488	0.224	−0.150	**−5.897**	**−6.304**
a_{4X}	0.006	−0.038	0.080	**−0.117**	−0.416	**−0.654**	−0.494	0.949	**1.094**
a_L			0.001			**−0.323**			**−1.248**
R^2	0.61	0.66	0.67	0.23	0.21	0.21	0.06	0.09	0.09

Table 2 continued

Parameter	Employment			Unemployment			Retail Sales		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
$\widetilde{\alpha}$	**0.024**	**0.027**	0.027	**0.082**	**0.068**	**1.926**	**0.665**	**0.602**	**0.602**
a_{1Y}	**0.227**	**0.233**	0.242	**0.981**	**1.018**	**0.987**	**−0.229**	**−0.212**	**−0.226**
a_{2Y}	**0.291**	**0.292**	0.294	**0.267**	**0.256**	**0.244**	**−0.122**	**−0.125**	**−0.116**
a_{3Y}	**0.210**	**0.199**	0.205	−0.052	−0.071	−0.044	0.069	0.048	**0.077**
a_{4Y}	**0.106**	**0.087**	0.088	**−0.209**	**−0.214**	**-0.199**	−0.022	−0.002	−0.007
$\widetilde{\alpha}_F$	**0.039**	0.029	0.025	**−0.063**	−0.003	−0.022	0.141	−0.001	−0.074
θ_1		1.127	1.121		1.010	1.005		3.604	**7.420**
θ_2		1.022	1.168		6.562	5.214		1.166	**49.713**
a_{1X}	0.018	**0.488**	0.318	0.001	−0.131	**−2.499**	−0.049	**−1.562**	**−0.498**
a_{2X}	−0.003	**0.327**	0.341	0.014	0.020	0.637	0.040	**2.114**	**−0.601**
a_{3X}	−0.013	−0.120	−0.209	−0.030	**0.109**	**2.196**	0.102	0.827	0.103
a_{4X}	−0.019	−0.082	−0.162	0.000	0.038	0.722	−0.014	**2.005**	−0.029
a_L			−0.002			0.520			−0.035
R^2	0.52	0.52	0.52	0.99	0.99	0.99	0.07	0.14	0.08

Table 2 continued

Figure 1: Data Plots Monthly Series

Data sources are described in Table 1. The series are: Coincident Index (CI-coincident), Leading Index (CI-leading), CPI: All Items (CPI-ALL) , CPI: Core (CPI-Core), Real Personal Income (RPI), Consumer Credit, Inflation Expectations, Industrial Production, Consumer Sentiment, Payroll Employment, Unemployment, Retail Sales

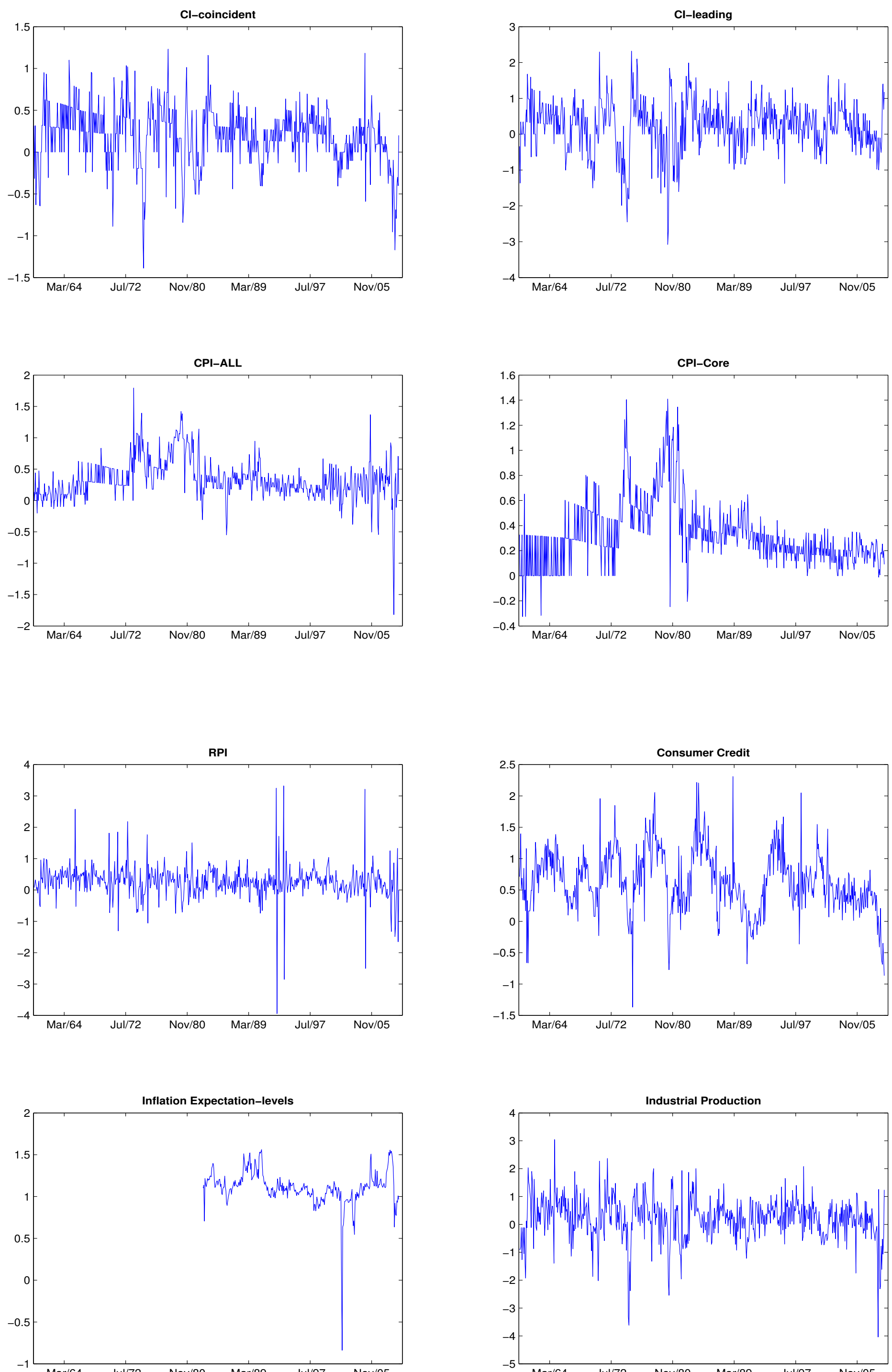

Figure 1 continued

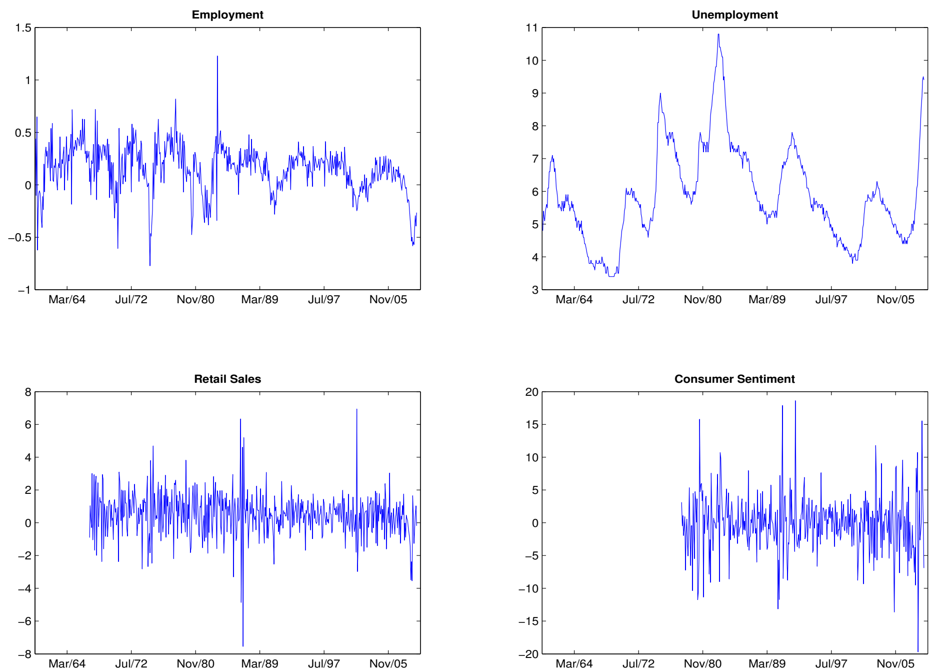

Figure 2: MIDAS weights for select variables

The plots display the estimated weights in equation (11) without restrictions on the MIDAS hyper-parameters, θ_1 and θ_2. Three representative series are covered: Leading Index (CI-leading), CPI Core and Consumer Credit.

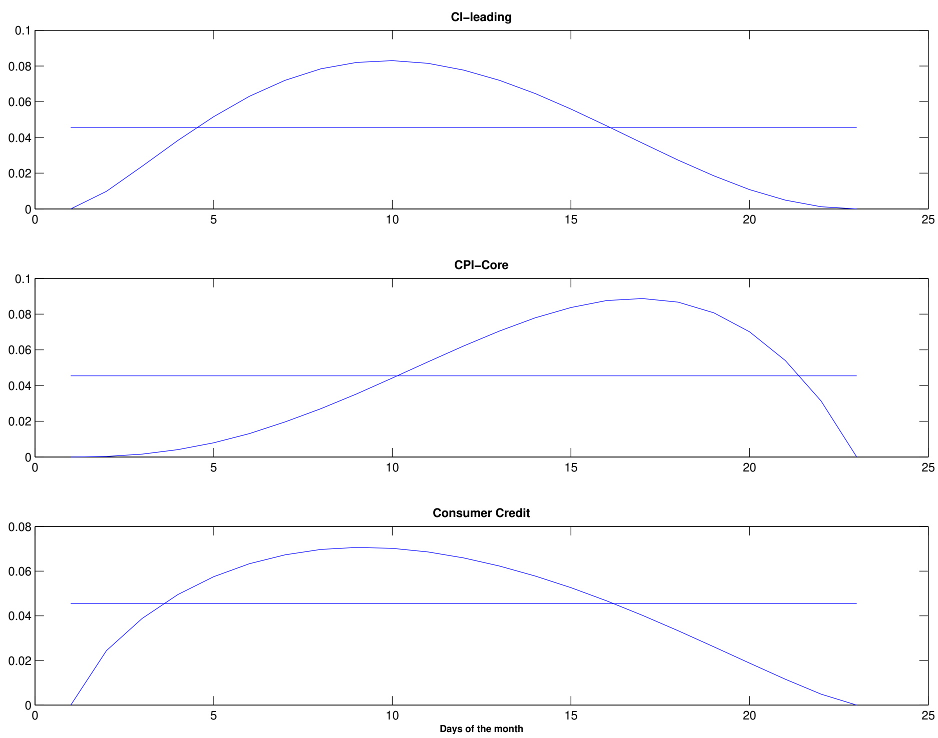

Figure 3: Impulse responses to an FOMC shock

Mean response to a 100-basis-point shock to the federal funds rate on the day of the FOMC calculated by local projection. 68-percent confidence intervals shown by shaded areas.

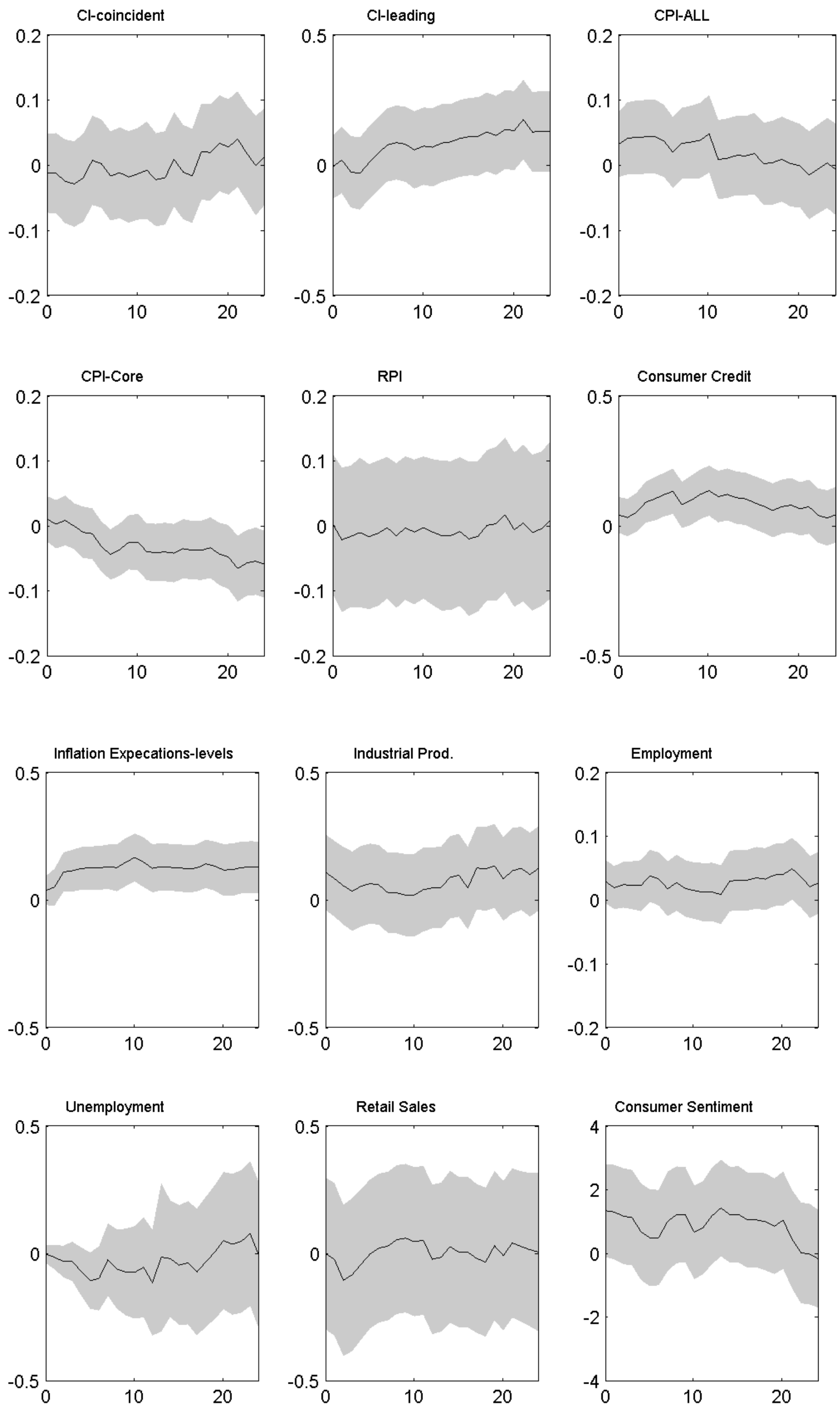

Figure 4: MIDAS impulse responses to an FOMC shock with standard VAR responses

Mean response (dotted line) to a 100-basis-point shock to the federal funds rate on the day of the FOMC calculated by local projection. 68-percent confidence intervals shown by shaded areas. The dashed-x line shows the median response computed by standard VAR methods.

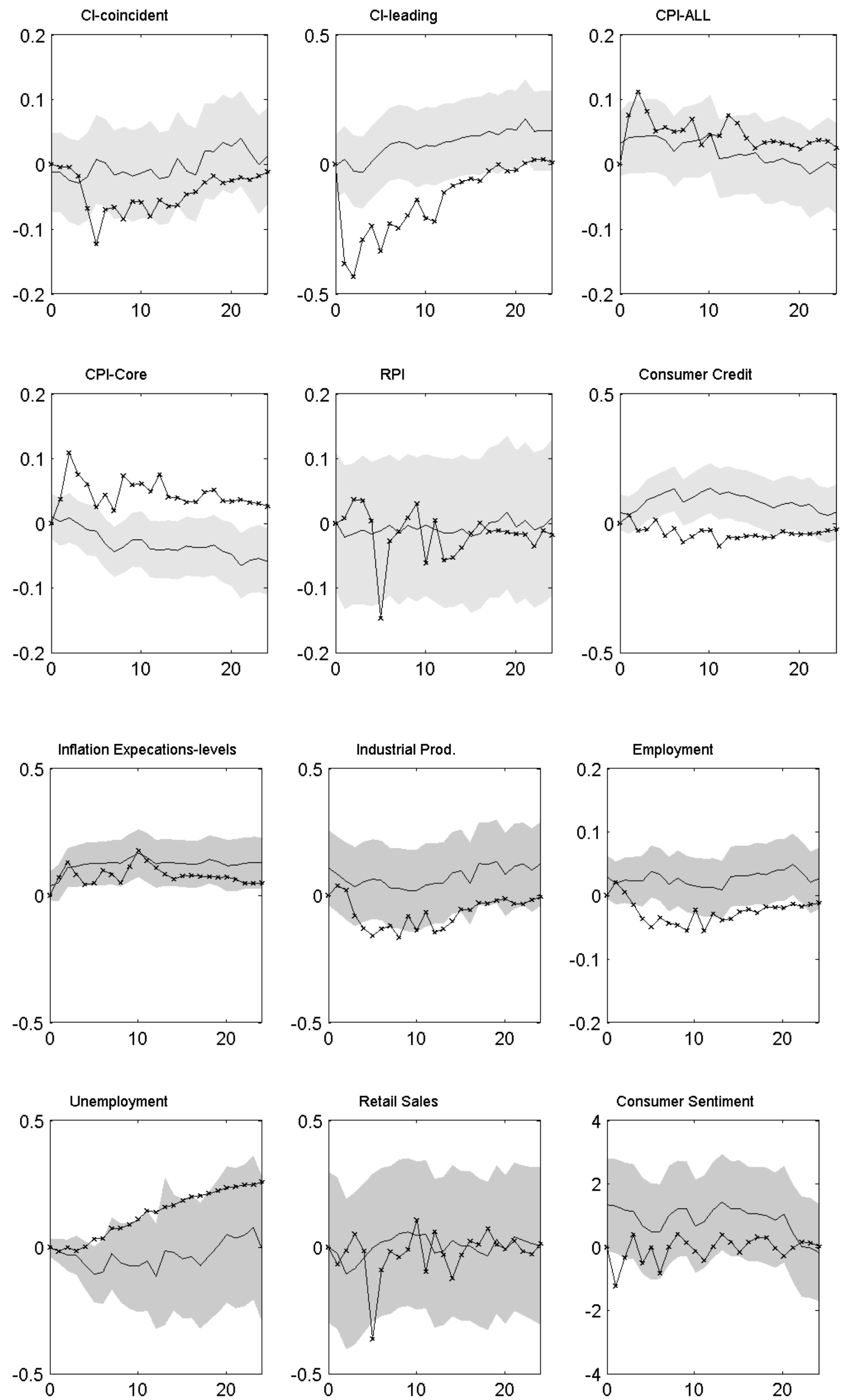

Figure 5: VAR impulse responses to an FOMC shock compared with MIDAS responses

We obtain three sets of impulse responses, one for each of the monetary policy shocks; *MIDAS*, *OLS*, and *Romer and Romer*. The figure contains plots of the three shocks over the sample period 1969:01 - 1996:12. The sample coverage is exactly that of Romer and Romer (2004). Mean response (dotted line) to a 100-basis-point shock to the federal funds rate on the day of the FOMC calculated by local projection. 68-percent confidence intervals shown by shaded areas. The dashed-x line shows the median response computed by standard VAR methods.

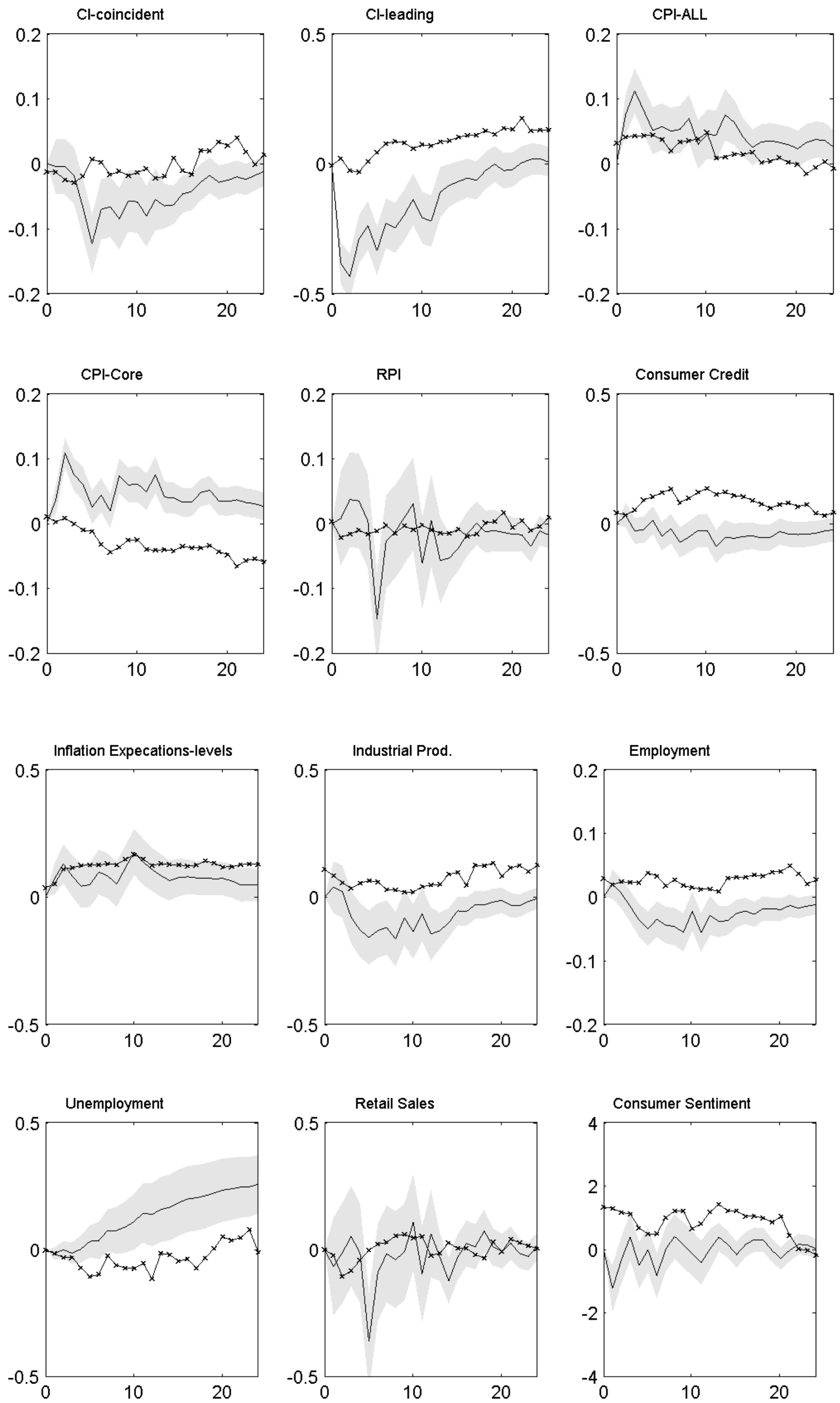

Figure 6: Monetary policy shock comparison

Romer and Romer (2004) devise a measure of monetary policy that purges changes in the fed funds rate around FOMC meetings of their *endogenous* and *anticipatory* components. The plot compares our daily monetary shocks with the series constructed by Romer and Romer over the sample period 1969:01 - 1996:12.

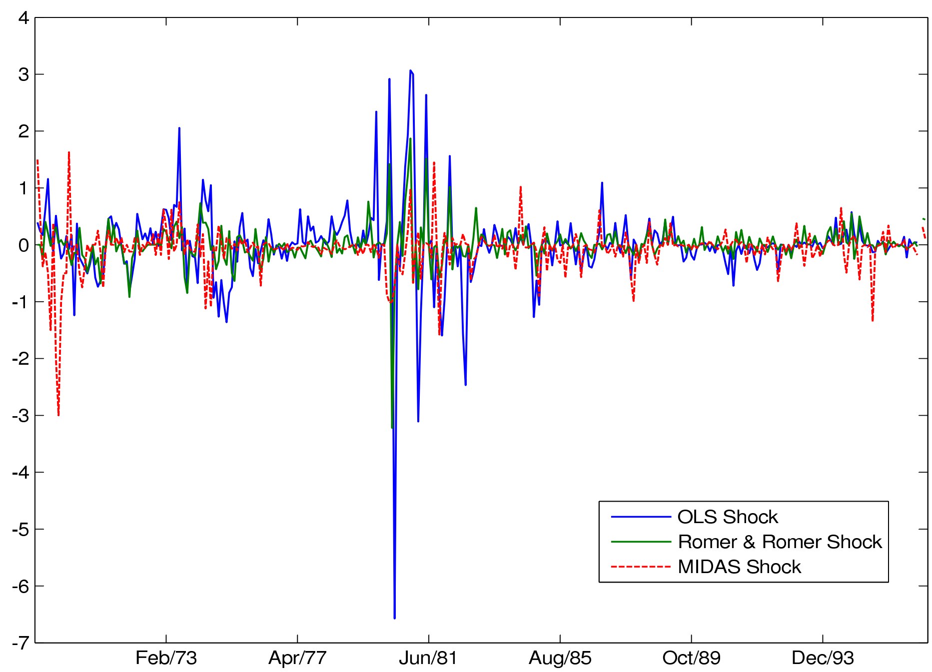

Figure 7: Robustness Plots

The figure plots the impulse responses to three monetary policy shocks over the period 1969:01 - 1996:12. The shocks used are: Romer Shock (identified around FOMC meeting days), OLS Shock (identified with a monthly Taylor -type regression), and Simple Autoregressive Shock (identified using daily federal funds rate data). The solid black line depicts the responses to the OLS shock, dashed-x line the responses to the Romer shock, and the dotted black line the responses to the simple AR shock. All figures were obtained via MIDAS on the daily interest rate data by replacing one measure of monthly monetary innovations with another.