What Information Do Proxy-VARs Use? A Study of High Frequency Identification in Macroeconomics

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Abstract

Many papers study effects of monetary policy shocks using high frequency surprises in asset prices around FOMC meetings. Allowing for time variation in the relationship between this instrument and the estimated policy shock, we show that only few distinct periods are informative about monetary policy shocks. Explicitly modeling this time variation thus builds a narrative for instrument-based identification. Filtering out uninformative periods can sharpen results: For the instrument in Gertler & Karadi (2015), the effect of monetary policy shocks on the (log) price level is 50 percent larger than the standard specification would suggest.

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1 Introduction

Identification of impulse responses via external instruments has become commonplace in empirical macroeconomics over the last decade (Mertens & Ravn 2013, Gertler & Karadi 2015). These external instruments are interpreted as imperfect measurements of unobserved structural shocks. A key assumption underlying studies that use this approach is that there is a fixed, time-invariant relationship between the instrument and the shock of interest. In this paper we present evidence that for a very common application of external instruments, the study of monetary policy shocks using high-frequency variation in asset prices around central bank announcements, there is actually substantial time variation in this relationship. To see this, Figure 1 plots the surprises in the three month ahead Fed Funds futures (FF4) in a 30 minute window around meetings of the Federal Open Market Committee (FOMC), a instrument popularized by Gertler & Karadi (2015) that we use as well.

There are periods where the dynamics of this instrument are substantially different from the rest of the sample - mainly the early 1990s, 2001 and during the Great Recession. We build a VAR model that explicitly captures this time variation, building on the Bayesian approach for VARs with instruments (commonly called proxy-VARs) by Caldara & Herbst (2019). Our model leaves intact the standard assumption of fixed coefficients in the structural VAR relationship itself (Baumeister & Hamilton 2015, Mertens & Ravn 2013, Caldara & Herbst 2019, Arias et al. 2021). This makes our approach and results directly comparable to the large majority of the structural VAR literature, in particular the part of the literature that uses external instruments.[1]

[1] Mumtaz & Petrova (2021) estimate time-varying parameter VARs with external

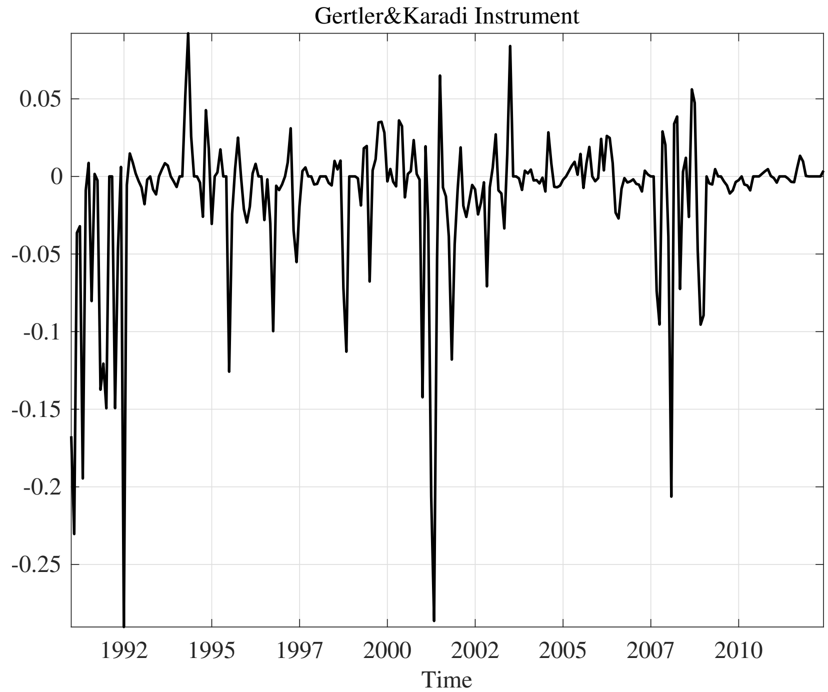

Figure 1: Surprise in 3 month ahead Fed Funds futures (Gertler & Karadi 2015)

Our approach yields two important insights. First, we can infer periods where the instrument is most informative about monetary policy shocks, thus helping to answer the question where identification is coming from and developing a narrative for identification. As such, our approach can be seen as complementing the narrative sign restrictions approach of Antolín-Díaz & Rubio-Ramírez (2018), who impose identification via sign restrictions (and related restrictions) for certain periods only. Our approach instead identifies informative periods for a given instrument. We find both for US and UK data that high frequency-based instruments for monetary policy shocks are only relevant for a small number of distinct periods. Second, because inference about the monetary policy shock is no longer contaminated by periods where the instrument is actually not

instruments, but in their application the relationship between the instrument and the shock of interest is actually time-invariant.

informative (our algorithm discounts information contained in the instrument from these periods), we can get a clearer view of the effects of monetary policy shocks: In our application using the same instrument as Gertler & Karadi (2015), the effects on prices can be 50 percent larger, for example. Error bands for impulse responses are generally *not* wider than their fixed coefficient counterparts. Even in applications where our approach yields similar impulse responses to the benchmark fixed coefficient approach (which is something that is not known a-priori), the sharpening of the identification narrative can be crucial for interpreting the results. Our approach comes at negligible additional computational cost relative to the previous literature.

The use of instruments in macroeconomics to identify the effects of monetary policy shocks has been pioneered by Romer & Romer (2004), who estimate a sophisticated monetary policy rule using real-time data and obtain their instrument as the residual in that estimated monetary policy rule. More recently, the focus has shifted towards the use of instruments based on high frequency variation in asset prices, first in event studies (Kuttner 2001, Gürkaynak & Wright 2013, Faust et al. 2007), and later as an instrument incorporated in time series models (Gertler & Karadi 2015, Jarociński & Karadi 2020, Caldara & Herbst 2019, Miranda-Agrippino & Ricco 2020), building on the work of Mertens & Ravn (2013), who introduced the proxy-VAR framework.[2] Wolf (2020) highlights how an instrument-based approach mitigates issues that can arise when using standard sign restrictions to identify monetary policy shocks, giving us even more reason to dig deeper into the underpinnings of this approach. Miranda-Agrippino & Ricco (2020) develop an instrument that is also

[2]The use of this type of identification is becoming more common: Känzig (2021) uses a high-frequency based identification to identify oil shocks.

based on high-frequency-based asset price variation around FOMC meetings, but further controls for information that the Federal Reserve had at the time of its meeting as well as possible autocorrelation in the instrument. We show in section 3.3 that with this instrument we also find relatively rare spikes in instrument relevance. Other papers directly use this instrument as a right hand-side variable for regressions to estimate the effects of monetary policy shocks (Campbell et al. 2016, Nakamura & Steinsson 2018).

The next section lays out our framework and discussed various modeling choices. Subsequent sections show results for the United States, robustness with respect to the instrument used as well as the modeling assumptions linking the instrument and the monetary policy shock, a Monte Carlo study using the Smets & Wouters (2007) model, and an application to UK data.

2 A VAR Model To Study Changes in Instrument Relevance

We want to study the response of a n dimensional vector of observables $\mathbf{y}_t$ to a monetary policy shock e_t^{MP}, which is one element of the n dimensional vector of structural shocks $\mathbf{e}_t$.[3] To estimate said response, we use the Structural Vector Autoregression (SVAR) in equation (1).

$$\mathbf{y}_t = \mathbf{c} + \sum_{\ell=1}^{\mathcal{L}} \mathbf{A}_\ell \mathbf{y}_{t-\ell} + \mathbf{\Sigma} \mathbf{e}_t \tag{1}$$

[3] We use boldface for vectors and matrices.

where $\mathbf{e}_t \sim_{iid} N(\mathbf{0}, \mathbf{I})$.

The well-known identification problem in Gaussian structural VARs (Canova 2011, Kilian & Luetkepohl 2018) implies that we need additional information to identify the column of the response matrix Σ that tells us how the elements of $\mathbf{y}_t$ respond to the monetary policy shock e_t^{MP}. The additional information we exploit, following a substantial fraction of the recent literature in empirical macroeconomics, is an instrument m_t for the monetary policy shock e_t^{MP}. There are various frequentist (Mertens & Ravn 2013, Stock & Watson 2018) and Bayesian (Arias et al. 2021, Caldara & Herbst 2019, Drautzburg 2020) approaches to incorporating such information in an SVAR analysis.[4] Since our ultimate goal is to study possible changes in the relationship between the observable m_t and the unobserved monetary policy shock, we explicitly state the relationship we want to estimate in equation (2).[5]

$$m_t = \beta_t e_t^{MP} + \sigma_m u_t^M \tag{2}$$

The key identification assumptions are twofold: First, we assume that u_t^M, which is distributed independently and identically over time as $N(0,1)$, is also independent of all other shocks in our model, both the vector of structural shocks $\mathbf{e}_t$ and any shocks determining the evolution of β_t, generally denoted as w_t. Second, the instrument is informative for the monetary policy shock - this means that at least for some periods $\beta_t \neq 0$. We

[4]Frequentist inference using proxies in dynamic factor models was introduced by Stock & Watson (2012).

[5]In section 3.3 we show that our results are robust when allowing for lagged macroeconomic variables to enter the right-hand side of equation (2), similar to specifications used in Arias et al. (2021) and Plagborg-Møller & Wolf (2021).

can formalize these assumptions as

$$E\left[e_{j,t} m_t\right] = 0 \quad \text{for } j = 2, \ldots, n. \qquad \text{(exogeneity)} \tag{3}$$

$$E\left[u_t^M \mathrm{e}_t\right] = 0 \quad \text{and} \quad E\left[u_t^M w_t\right] = 0 \tag{4}$$

$$E\left[e_t^{MP} m_t\right] = \beta_t \neq 0 \quad \text{for some } t. \qquad \text{(relevance)} \tag{5}$$

where $e_{j,t}$ denotes the j-th element of e_t and w_t is the time t innovation to β_t.

Our Bayesian estimation approach will still be valid if $\beta_t = 0 \quad \forall t$. In that case the impulse responses are not identified. In particular, our approach will automatically approximate the posterior distribution of β_t and the associated instrument reliability for each time period t. If those are always small (i.e. standard posterior bands include 0), we can infer that the instrument is weak.[6]

We borrow this approach of directly estimating the parameters of this measurement equation from Caldara & Herbst (2019). Different from that paper, we allow for changes in the parameter β_t governing the systematic relationship between these two variables.

A useful summary statistic to assess the strength of the instrument in different periods is a time-varying version of the common reliability (or relevance) statistic ρ_t:

$$\rho_t \equiv \frac{\beta_t^2}{\beta_t^2 + \sigma_m^2} \tag{6}$$

This statistic represent a time-t approximation to the squared correlation between the instrument and the structural shock - the approximation is

[6] Our approach also assumes invertibility of the monetary policy shock. For our monetary policy application, this seems to be a widely accepted assumption (Wolf 2020). For recent work on the link between inference using instruments and invertibility, see Miranda-Agrippino & Ricco (2022).

exact if parameters are constant.

We will estimate three specifications for β_t: (i) a constant parameter specification reminiscent of Caldara & Herbst (2019) as a benchmark (equation (7)), (ii) a random walk specification in the tradition of the literature on time varying parameters in state space models and VARs (Cogley & Sargent 2002, Primiceri 2005, Stock & Watson 2007), and (iii) a Markov-switching specification that allows for infrequent changes in β_t (Hamilton 1989, Sims & Zha 2006). We assume that any random innovations to β_t are independent of u_t^M and e_t.

$$\text{Constant: } \beta_t = \beta \tag{7}$$

$$\text{Random Walk: } \beta_t = \beta_{t-1} + \sigma_\beta w_t, w_t \sim_{iid} N(0,1) \tag{8}$$

$$\text{Markov Switching: } \beta_t = \beta_{s_t}, Pr(s_t = i | s_{t-1} = j) = p_{ij} \tag{9}$$

To approximate the posterior of our model, which consists of equations (1), (2), and one of the equations (7), (8), or (9), we modify the Metropolis-within-Gibbs sampling framework of Caldara & Herbst (2019) (the specification with equation (7) is exactly their specification). One important feature of our algorithm is that we do not require the same number of observations for the instrument m_t as for the macro variables collected in y_t. Details about the algorithm can be found in Appendix A.

Two possible extensions of our model are immediate. First, instead of one instrument, we could use multiple instruments. In that case we would need to make a decision about possible correlation in the error terms of the measurement equations for example. Since in our application the instruments yield similar results when used on their own we don't pursue this extension here.

More importantly, we could allow for stochastic volatility in the law of motion for the parameter β_t.[7] If we had introduced stochastic volatility in equation (2) instead of time varying parameters, this would change how our model interprets spikes in the instrument. Our current assumption means that spikes or outliers are interpreted as informative events - with stochastic volatility they would be interpreted as noise. In most of our applications (both for US and UK data) it turns out that the instruments are generally not very informative (low ρ_t) except for clearly delineated short periods of high reliability. Thus using stochastic volatility would imply a prior that in these specific applications would put very little faith in the instruments.[8] This stands in contrast to standard priors in the proxy-VAR literature (Arias et al. 2021, Caldara & Herbst 2019) that impose a prior that implies that the instruments are indeed useful/reliable. Our assumption of time-varying parameters is thus best seen as a context-specific prior choice that implies that there is at least *some* instrument reliability, in line with the previous literature. We will show in the following sections that the periods our algorithm identifies as informative are generally those anecdotal evidence also identifies as periods where there was substantial uncertainty about the conduct of monetary policy and hence meaningful monetary policy shocks. We also show in Section 4 via Monte Carlo experiments that our approach does as well as the standard fixed coefficient approach when it is misspecified and there is either

[7]One could also, along the lines of Mumtaz & Petrova (2021), introduce stochastic volatility in equation (1). If the changes in volatility in our instrument (see Figure 1) would be due to actual changes in the volatility of monetary shocks, we would expect to estimate a relatively smooth evolution of β_t, which is not what we find in our applications.

[8]Results with stochastic volatility will thus give similar results to one of the robustness checks in section 3.2.

stochastic volatility in the measurement equation that is unrelated to monetary policy or if there is stochastic volatility in the monetary policy shock.

3 The Effects of Monetary Policy Shocks Identified via High Frequency Variation in Asset Prices

In this section, we first contrast the constant parameter specification with the random walk specification. Our main application uses US data: y_t consists of the log of the Consumer Price Index (CPI), the log of Industrial Production (IP), the interest rate on 1 year government bond yields, as well as the Excess Bond Premium (Gilchrist & Zakrajsek 2012). As Caldara & Herbst (2019) highlight, including a measure of financial conditions like the Excess Bond Premium in our VAR is crucial to get the effects of monetary policy right. The sample for y_t runs from July 1979 to June 2012. We follow Gertler & Karadi (2015) in our choice of the instrument m_t and use the surprise in the 3 month ahead Fed Funds futures around FOMC meetings (the series depicted in Figure 1). The sample for m_t is January 1991 to June 2012.

We use 12 lags in our VARs in this paper. The priors we use throughout are standard in the literature. We make the priors as comparable as possible across the different specifications: The same parameters always have the same priors. Furthermore, the prior for β in the fixed coefficient variant is the same as the prior for β_0 in the random walk specification. Estimation results for models with time varying coefficients can be somewhat sensitive to the choice of prior for the innovation standard deviation σ_β in the law of motion for the parameter - this parameter governs the amount of time variation. This is less of an issue here because (i) we only have one time-varying parameter (in contrast to papers where all VAR parameter can vary, such as Cogley & Sargent (2002), Primiceri (2005), and (ii) we don't have stochastic volatility in our model, which helps sharpen inference. Nonetheless, to make sure that this is not an issue, we follow some of our previous work (Amir-Ahmadi et al. 2020) and estimate the hyperparameters that enter the prior for σ_β.Details on the priors can be found in Appendix A.

Figure 2 shows the posterior path of β_t and ρ_t. In gray we plot the corresponding elements of the fixed coefficient version. We plot the posterior median as well as 68 percent equal-tail posterior bands.[9]

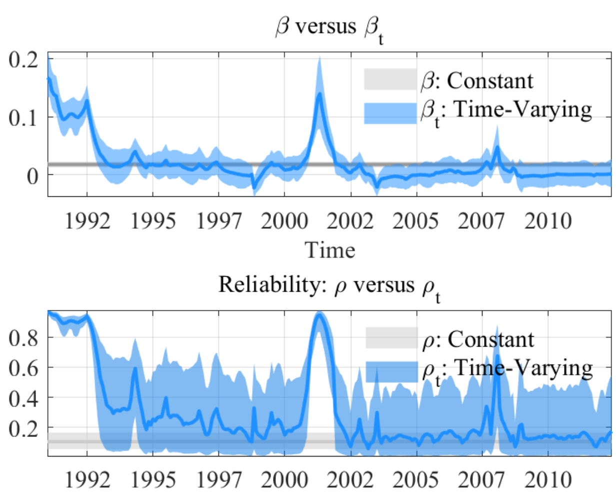

Figure 2: Posterior of β_t and ρ_t (median and 68 percent posterior bands).

It is striking that there are few short periods of high instrument relevance when allowing for time variation in β. First, the first half of the 1990s stands out. This large value of β_t is not driven by our prior as our

[9]Any posterior bands in this paper are 68 percent posterior bands.

prior for the initial value of β_t is centered at 0. Instead the first half of the 1990s was characterized by relatively high inflation at the beginning as well as a (mild) recession. Our model highlights the period coming out of the 1990s recession when annual CPI inflation was still high in 1991 (4.2 percent) as a period where the Federal Reserve was surprisingly accommodative (see Figure 1). The second period our model highlights is around September 2001. Not surprisingly, the exact actions of the Federal Reserve where hard to predict around that time even though the direction was clear. Finally, Great Recession around 2008 is the third period of high instrument relevance. Our framework thus helps us understand what information is contained in instruments.

Does this time variation in instrument relevance matter for impulse responses? Figure 3 shows the impulse to a one standard deviation monetary policy shock under the fixed coefficient (gray) and random walk (blue) specifications. We plot the posterior median as well as 68 percent error bands. For bond yields, IP, and the Excess Bond Premium the impulse responses are similar. For log CPI, the differences are, instead, *substantial*. With fixed coefficients, we see a price puzzle appearing, whereas this is not the case at all for the posterior median of the impulse responses when we allow for time variation in instrument relevance. Furthermore, the response of log CPI is larger in magnitude - after 4 years the posterior median of the response is 50 percent larger when we allow for time variation in instrument relevance. Our approach discounts periods where the instrument is not informative and hence can lead to substantially different impulse responses. As mentioned, before, this does not come at a cost in terms of the width of the error bands in our example.

Looking back at Figure 2, one possible criticism could be that the estimated path for β_t might be better characterized by a Markov switching model. We think of the random walk as our benchmark exactly because it is flexible enough to approximate many patterns of time variant, including sudden changes as observed in Figure 2. Nonetheless, we estimate a two-state Markov-switching specification next and show that it yields very similar results.

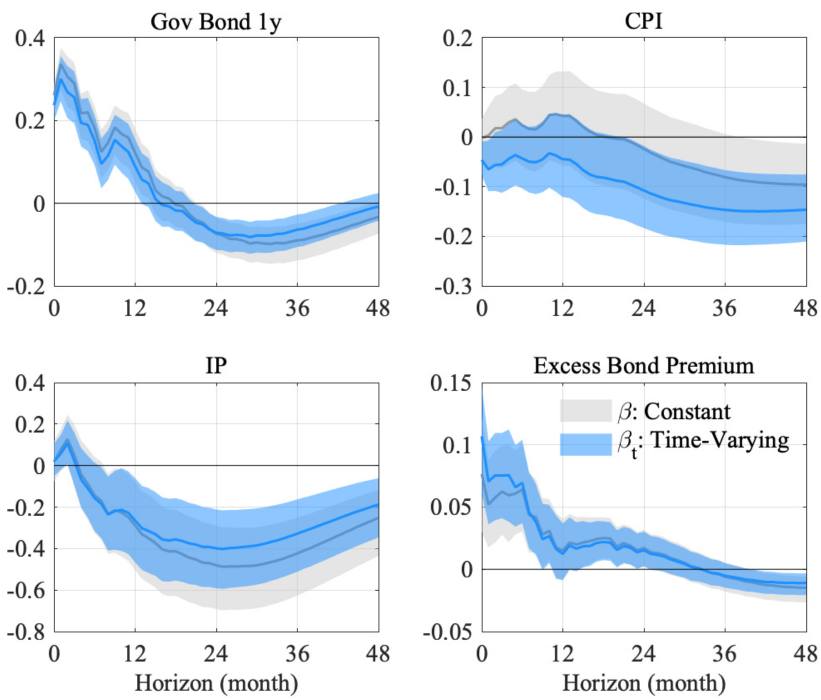

Figure 3: Impulse responses (median and 68 percent posterior bands) to a one standard deviation monetary policy shock.

3.1 A Markov-Switching Alternative

The only difference between the Markov-switching specification and the random-walk benchmark is the law of motion for β_t as detailed in equations (8) and (9) respectively.

Figure 4 shows the impulse response of log CPI to a one standard deviation monetary policy shock in the two-state Markov-switching model for β_t. We focus here on the response of CPI because that is where the major differences between fixed coefficient and time varying parameter results occured in the previous section. That impulse response is very similar to the random walk specification. Figure 5 plots instrument relevance

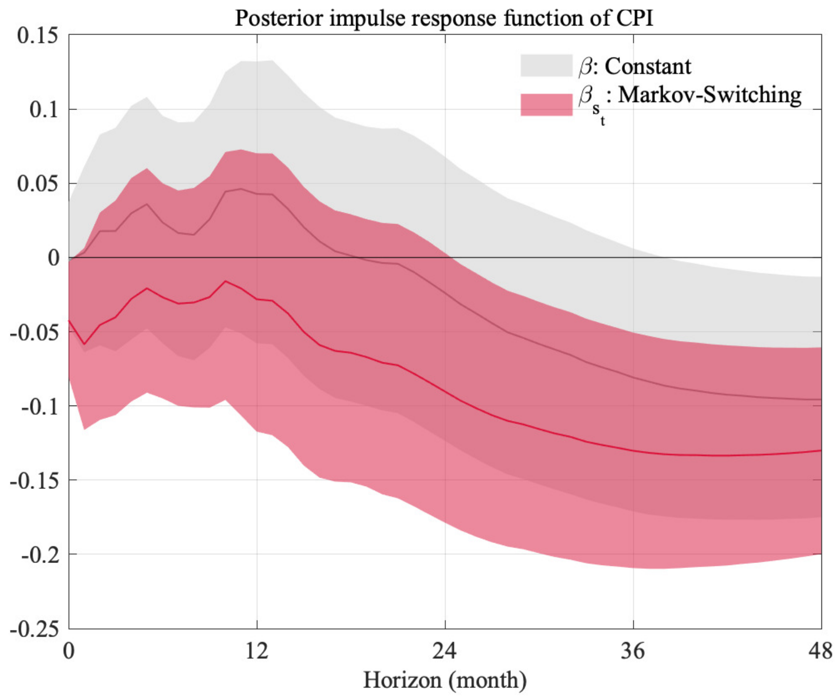

Figure 4: Impulse response of log CPI for Markov-switching specification (median and 68 percent posterior bands).

for our benchmark random walk specification in blue and the two-state Markov-switching model in red. We can see that both specifications identify largely the same periods of high instrument relevance. The random walk specification is somewhat conservative in that it has less spikes, but this does not lead to any meaningful difference in impulse responses, as discussed above. The choice for a specific law of motion for β ultimately comes down to the application in mind as well as preferences. We recommend the random walk as a default choice because of its flexibility.

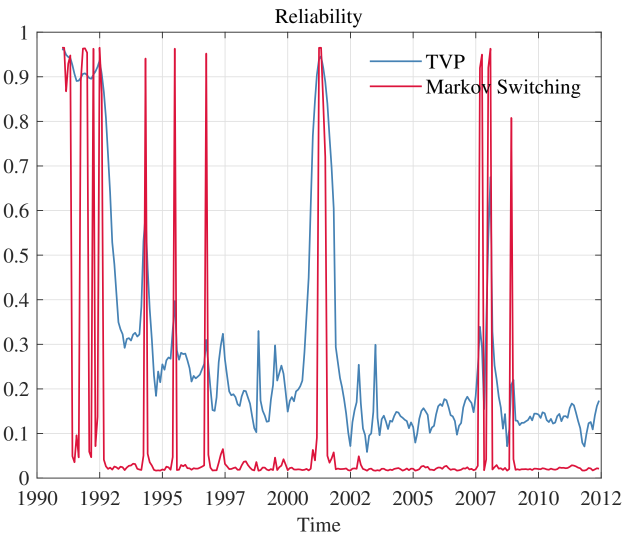

Figure 5: Posterior reliability for Markov-switching and random-walk specifications (posterior median).

3.2 Shutting Down Periods Where the Instrument is Informative/Not Informative

To get a better sense of the role periods with high instrument relevance play in shaping the posterior distribution of the impulse responses, we now carry out two diametrically opposite thought experiments. First, we compute the posterior probability that $\beta_t = 0$ for each time period t, using the approach in Koop et al. (2010) and our original instrument m_t. We then create two instruments, $\tilde{m}_t$ and $\overline{m}_t$, from our instrument according to the following two rules:

1. $\tilde{m}_t = m_t$ if $Pr(\beta_t = 0) < 0.5$, $\tilde{m}_t = 0$ else
2. $\overline{m}_t = m_t$ if $Pr(\beta_t = 0) \geq 0.5$, $\overline{m}_t = 0$ else

$\tilde{m}_t$ only keeps the original realizations of our instrument of our model deems these realizations informative, whereas $\overline{m}_t$ only keeps relatively uninformative realizations. The threshold probability of 0.5 only selects the early 1990s and 2001 as periods that are informative.

Figure 6 shows the results when we use $\tilde{m}_t$ as our instrument. For the sake of comparison, the fixed coefficient VAR in that figure uses our original instrument m_t. We see that our approach still estimates the same periods to have high instrument relevance.[10] The impulse responses (we highlight CPI in this figure, but show all responses in the Appendix) are very similarly to our original setting. This makes clear that it is indeed *only* those high instrument relevance periods that inform the impulse responses. Naturally, this result depends on the specific application. Had the instrument relevance been reasonably high outside of the spikes in instrument relevance we document, the procedure in this section would have lead to meaningful loss of information.

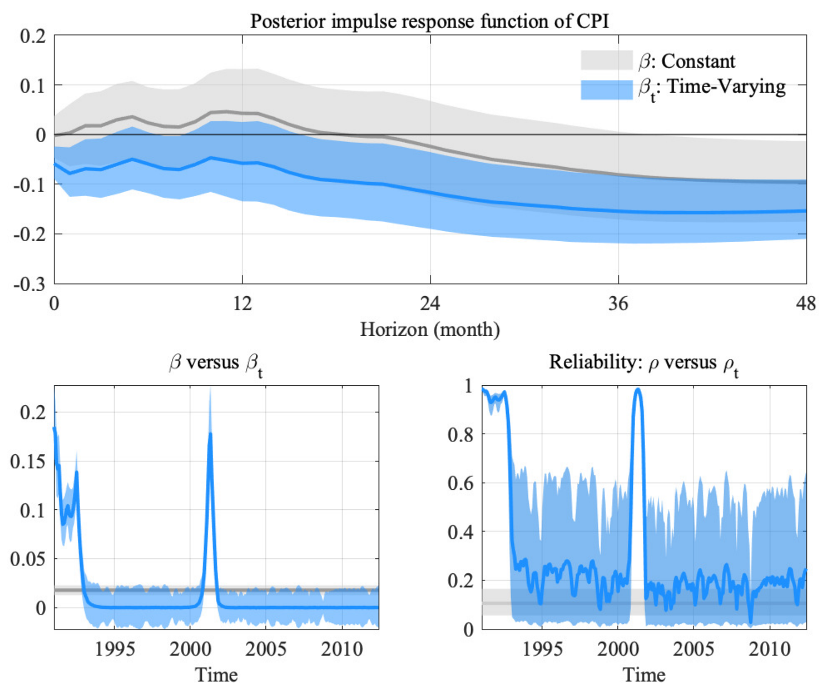

Figure 6: Results for $\tilde{m}_t$ (median and 68 percent posterior bands). Fixed coefficient VAR based on original m_t instrument.

Figure 7 plots the corresponding results when we only keep the origi-

[10]To economize on notation, we also call this parameter β_t, but it is a different object from β_t when we use the instrument m_t.

nal instrument if its relevance is low. 0 is now included in the 68 percent posterior bands for all horizons. Posterior instrument relevance is low for all periods. Even though we keep 90 percent of the observations from the original sample, there is little information contend in those observations.

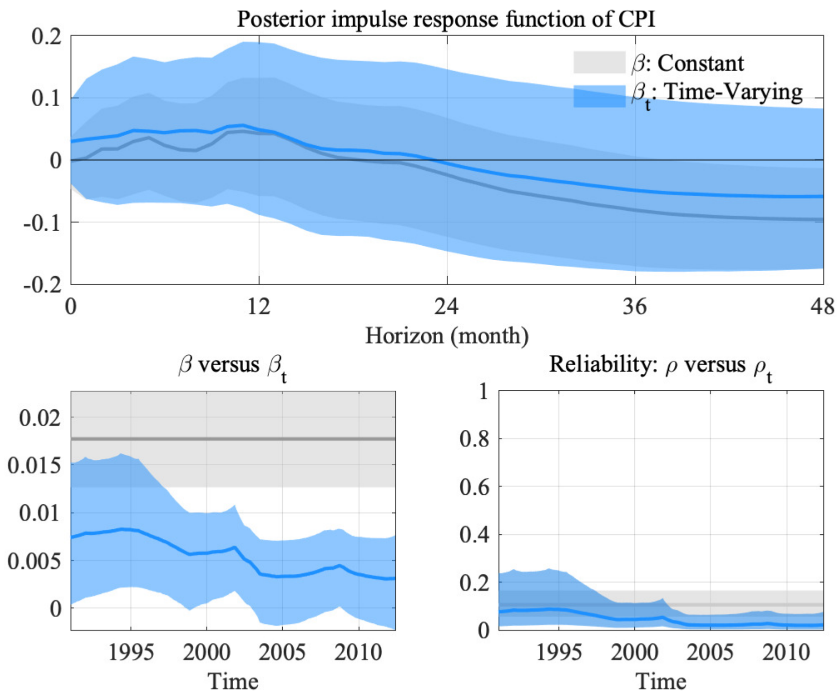

Figure 7: Results for $\overline{m}_t$ (median and 68 percent posterior bands). Fixed coefficient VAR based on original m_t instrument.

3.3 Alternative Instruments

Our various observation equations linking m_t and the unobserved monetary shock all imply that m_t is iid, borrowing from Caldara & Herbst (2019). Other papers in the literature have posited more flexible relationships where the instrument can be contaminated by past macro variables and or lags of the instrument. To asses whether this is an issue in our application, we progress in two steps. First, we regress our instrument on 2 lags of itself and the variables y_t in the VAR . The key results are summarized in Figure 8. We see that the results are very similar to our benchmark. The only difference is that the spike in ρ_t and β_t surrounding the Great Recession is less pronounced. The impulse response of CPI is basically unchanged (other impulse responses can be found in Appendix B).

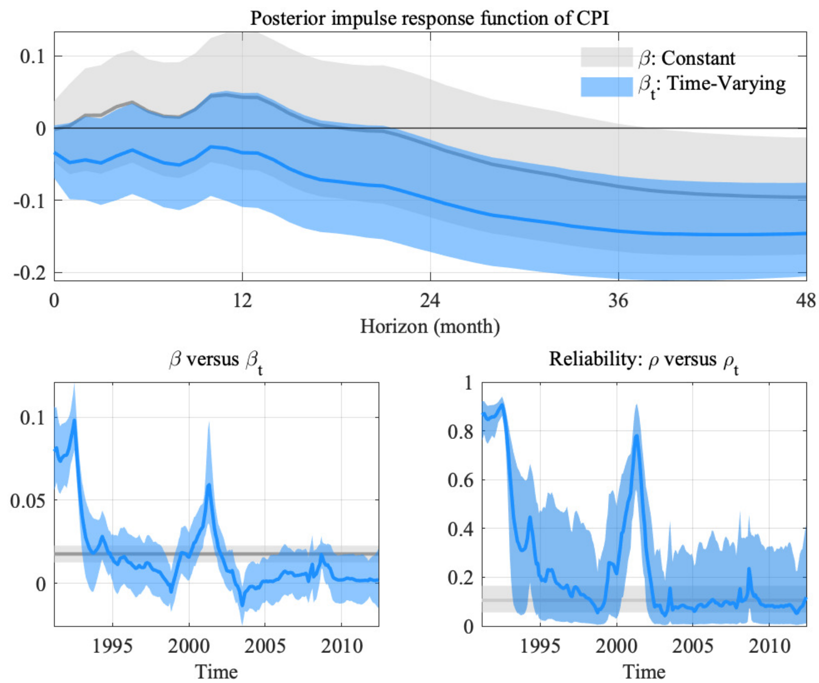

Figure 8: Results for the case of the modified instrument (median and 68 percent posterior bands).

Second, we use the instrument introduced by Miranda-Agrippino & Ricco (2020). The authors start off with a high-frequency-based instrument like our benchmark choice, but then remove any autocorrelation and information available to the FOMC at the time of their meetings (as encoded in the Greenbook).[11] The sample for this instrument is January 1991 to December 2009 - it is shorter due to the need for Greenbook data,

[11] As highlighted recently by Bauer & Swanson (2022), in this context the information content of professional forecasts is very similar to those forecasts contained in the Greenbook.

which is published with a lag. Figure 9 shows that for this instrument, the largest spike in β_t by far is now around 2001. We still see a clear tightening of the error bands for instrument reliability in the early 1990s and around the Great Recession as well, but these movements are less pronounced than in our benchmark. Interestingly, the posterior median path of instrument reliability is substantially higher than in our benchmark or in Figure 9. Since the reliability does not fall as much between spikes as in our benchmark, it is not surprising that the difference between the fixed coefficient version of the impulse response of log CPI and its random walk counterpart are very similar - and both are similar to the random walk-based results form our benchmark instrument. While using our approach with the Miranda-Agrippino & Ricco (2020) instrument does not change the conclusions in terms of impulse responses, it adds substantial interpretability: For example, the most informative period (largest β_t value and largest instrument reliability) is around 2001.

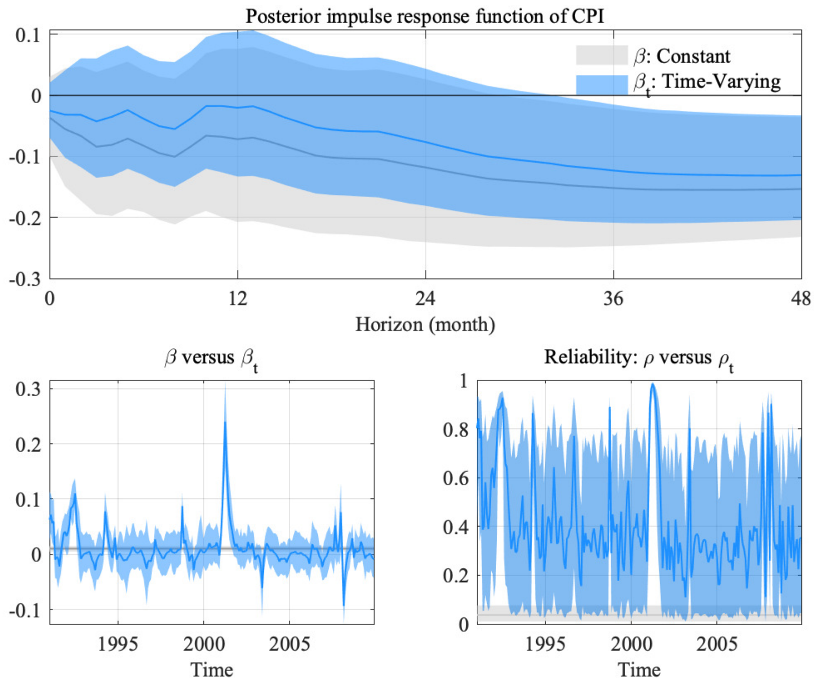

Figure 9: Results for the Miranda-Agrippino & Ricco (2020) instrument (median and 68 percent posterior bands).

4 A Monte Carlo Study

To assess the properties of our approach, we now turn to a series of Monte Carlo experiments (details on the exact calibration of the data-generating processes can be found in Appendix C). As a laboratory, we follow Wolf (2020) and use the Smets & Wouters (2007) model.[12] We use three observables in our VAR: output, inflation and nominal interest rates. Since the Smets-Wouters model is a quarterly model we set the lag length in our VAR to 4. The first Monte Carlo experiment uses time variation in the measurement equaiton of the instrument that is along the lines of our estimated models: The data-generating process features parameter

[12]Wolf (2020) studies an instrumental variables approach in VARs, but besides his assumption of fixed coefficients, there are two substantial differences relative to our setup: We use a standard sample size in our simulations (whereas Wolf (2020) studies population properties) and we introduce measurement error in our instrument, which we calibrate to have 25 percent of the variance of the actual monetary shock.

changes in β_t. We choose an extreme scenario where β_t can only take on the values 0 and 1. The path of β_t in the data-generating process is fixed across all Monte Carlo samples.

We simulate 100 samples of length 250 using the posterior mode, as

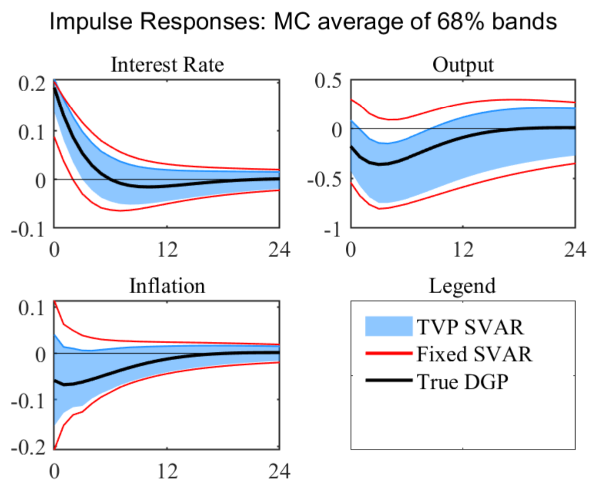

Figure 10: Impulse responses for the DGP and the Monte Carlo replications.

in Wolf (2020). For 13 percent of those periods[13] we set $\beta_t = 1$ in the data-generating process, otherwise it is 0 (and the instrument hence just noise). Figure 10 shows the true impulse response to a one standard deviation monetary shock in black as well as the Monte Carlo average of the 68 percent posterior bands for our approach and the fixed coefficient version. Our results confirm those of the population analysis in Wolf (2020): even without perfect invertibility, the true responses are well approximated by our VAR. The fixed coefficient version generally has wider error bands - this leads the average posterior bands for output to include 0 for all horizons and a more pronounced probability of a price puzzle for inflation.

Figure 11 shows the estimated posterior median of instrument reliabil-

[13]From periods 1 to 4, 141 to 149, and from 231 to 250.

ity in blue and the true reliability path in black. Our approach captures changes in instrument reliability extremely well. Next we turn to two

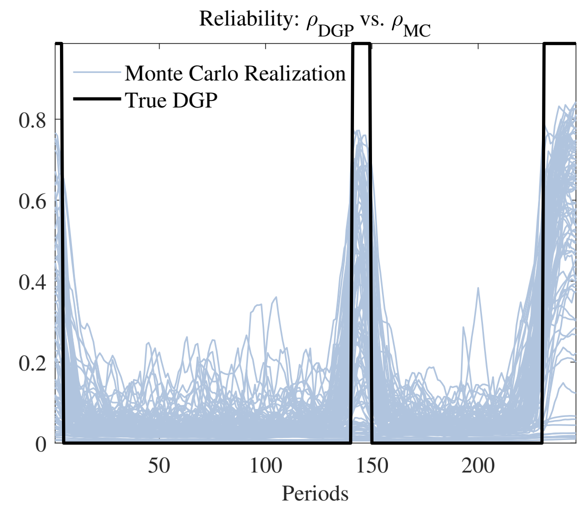

Figure 11: Reliability for the DGP and the Monte Carlo runs (posterior medians).

Monte Carlo experiments where our specification of the measurement equation for the instrument is misspecified. We focus here on the estimated impulse responses - the estimated reliability does not vary much in both of these cases. First, we simulate data so that there is stochastic volatility in the measurement error u_t^M. We choose parameter values to keep the overall volatility of the instrument at each point in time to be the same as in the benchmark case discussed just before. Figure 12 shows that our approach does as well as the fixed coefficient version that is standard in the literature even though both are misspecified in different ways.

Finally, we ask how our approach fares when confronted with data where there is stochastic volatility in the true monetary policy shock.[14] We again keep the paths of the volatility of the instrument the same as in

[14]We solve the model linearly and then change the volatility of the monetary policy shock in some periods, along the line of Justiniano & Primiceri (2008).

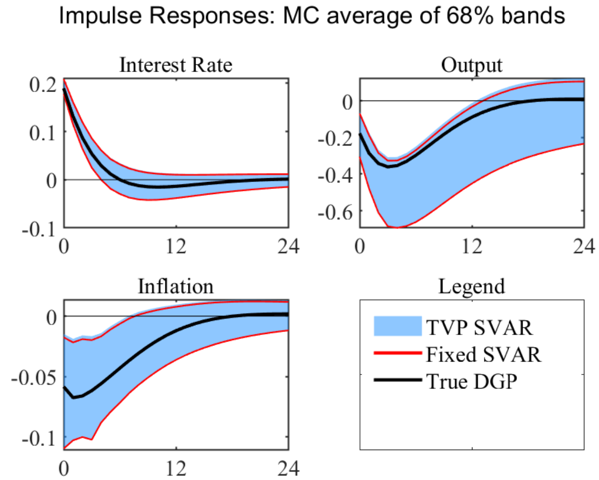

Figure 12: Impulse responses for the DGP and the Monte Carlo replications - stochastic volatility in the measurement error.

our benchmark specification. Figure 13 shows that our approach again does as well as the fixed coefficient version.

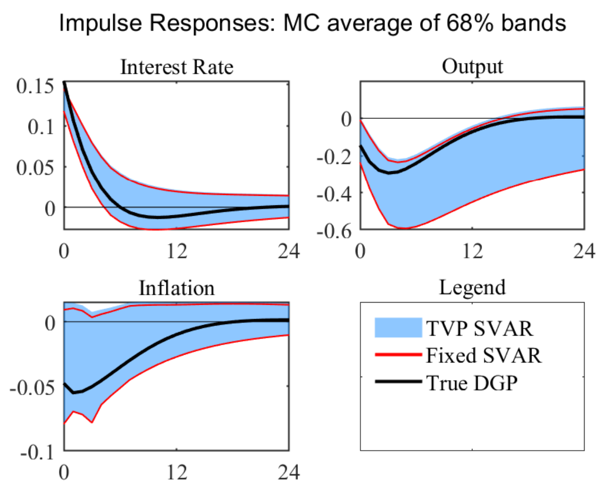

Figure 13: Impulse responses for the DGP and the Monte Carlo replications - stochastic volatility in the monetary policy shock.

5 Evidence from the UK

Finally, we present evidence for high-frequency based identification of monetary policy shocks in the United Kingdom. We use both the instrument and the VAR specification (i.e. the choice of variables entering y_t) of Cesa-Bianchi et al. (2020).

Figure 14 shows impulse responses for 4 selected UK variables. In contrast to the US, we find little difference between fixed coefficient-based responses and random walk-based responses. A potential reason can be seen in Figure 15: the sample for the UK (both for the VAR variables and the instrument) is much shorter, and within that shorter time-span there are more periods where the instrument is informative, making the fixed coefficient estimation generally more informative.

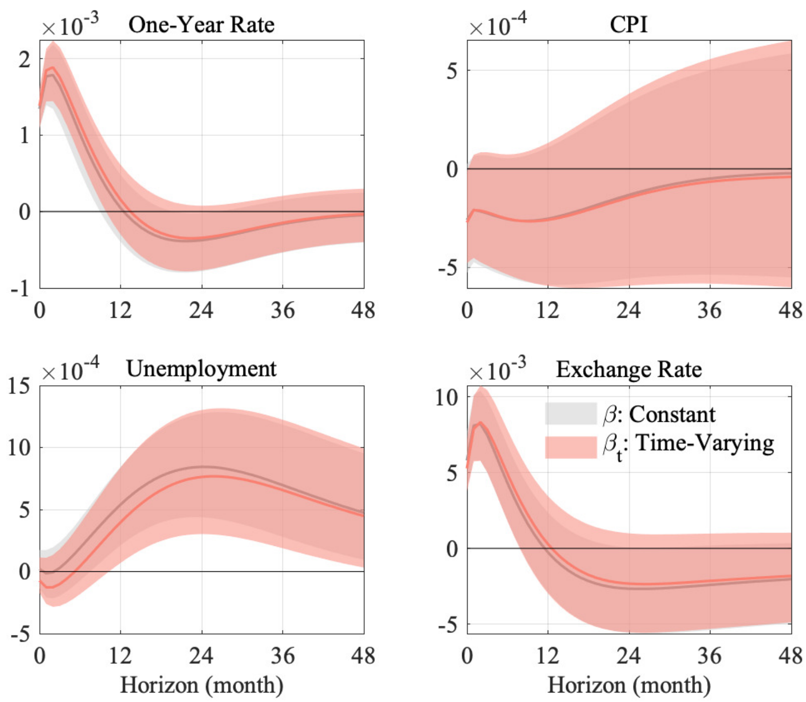

Figure 14: Impulse responses (median and 68 percent posterior bands) to a one standard deviation monetary policy shock, UK.

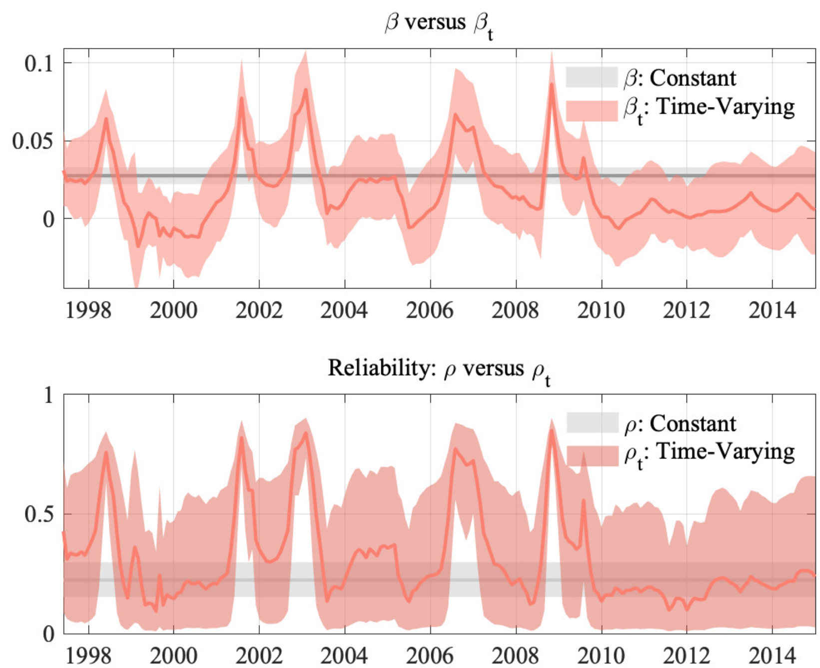

Figure 15: Posterior of β_t and ρ_t, UK (median and 68 percent posterior bands).

6 Conclusion

We study how instrument relevance changes over time in a common application of instrument-based identification in structural VARs.Our approach allows us to isolate periods where instruments are informative, helping build a narrative for a given instrument. Furthermore, our can substantially alter conclusions by discounting periods where the instrument is not informative, as in the case of the Gertler & Karadi (2015) instrument. While we focus in our application on monetary policy shocks, the estimation approach we develop is general and can be used for any application of external instruments in VARs.

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A Algorithms and Priors

A.1 Random Walk Specification

The first three steps of the algorithm follows exactly Algorithm 1 of Caldara & Herbst (2019), whose notation we borrow. The law of motion of β_t is given by

$$\beta_t = \beta_{t-1} + w_t \overset{iid}{\sim} N\left(0, \sigma_w^2\right).$$

In addition, we assume following priors:

$$\begin{aligned} p\left(\sigma_w^2\right) &\sim IG(\tau/2, \tau\kappa/2). \\ p(\beta_0) &\sim N(b_0, V_0). \end{aligned}$$

The scale parameter κ of the IG prior is crucial for controlling the time variation. We follow the procedure outlined in Amir-Ahmadi et al. (2020) to estimate this parameter.

Algorithm 1. For $i = 1, \ldots, N$. At iteration i

1. Draw $\Sigma, \Phi \mid \mathbf{Y}_{1:T}, \mathbf{M}_{1:T}, \Omega^{i-1}, \beta_{1:T}^{i-1}, \sigma_m^{i-1}, \sigma_w^{i-1}, \kappa^{i-1}$. For Σ we use a mixture proposal distribution (suppressing dependence on parameters for notational convenience):

$$q\left(\Sigma \mid \Sigma^{i-1}\right) = \gamma p\left(\Sigma \mid \mathbf{Y}_{1:T}\right) + (1-\gamma)\mathcal{IW}\left(\Sigma; \Sigma^{i-1}, d\right)$$

   where $p\left(\Sigma \mid \mathbf{Y}_{1:T}\right)$ is the known posterior distribution of $\boldsymbol{\Sigma}$ under $\mathbf{Y}_{1:T}$ and $\mathcal{IW}\left(\cdot; \Sigma^{i-1}, d\right)$ is an Inverse Wishart distribution with scaling matrix Σ^{i-1} and d degrees of freedom. For Φ we use the known distribution $p\left(\Phi \mid \mathbf{Y}_{1:T}, \Sigma\right)$ as a proposal in an independence MH step:

- Draw Σ^* according to $q\left(\Sigma \mid \Sigma^{i-1}\right)$.
- Draw Φ^* according to $p\left(\Phi \mid \mathbf{Y}_{1:T}, \Sigma^*\right)$.
- With probability α, set $\Phi^i = \Phi^*$ and $\Sigma^i = \Sigma^*$, otherwise set $\Phi^i = \Phi^{i-1}$ and $\Sigma^i = \Sigma^{i-1}$, defined as

$$\alpha = \min\left\{\frac{p\left(\mathbf{M}_{1:T}, \mathbf{Y}_{1:T}, \Phi^*, \Sigma^*, \Omega^{i-1}, \beta^{i-1}, \sigma_\nu^{i-1}\right) p\left(\Sigma^*\right)}{p\left(\mathbf{M}_{1:T}, \mathbf{Y}_{1:T}, \Phi^{i-1}, \Sigma^{i-1}, \Omega^{i-1}, \beta^{i-1}, \sigma_\nu^{i-1}\right) p\left(\Sigma^{i-1}\right)} \frac{q\left(\Sigma^{i-1} \mid \Sigma^*\right)}{q\left(\Sigma^* \mid \Sigma^{i-1}\right)}, 1\right\}$$

2. Draw $\Omega \mid \mathbf{Y}_{1:T}, \mathbf{M}_t, \Omega^{i-1}, \beta_{1:T}^{i-1}, \sigma_m^{i-1}, \sigma_w^{i-1}, \kappa^{i-1}$. Use an Independence Metropolis-Hastings sampler step using the Haar measure on the space of orthogonal matrices:

   - Draw Ω^* using Theorem 9 in Rubio-Ramírez et al. (2010).
   - With probability α, set $\Omega^i = \Omega^*$, otherwise $\Omega^i = \Omega^{i-1}$ is defined as

$$\alpha = \min\left\{\frac{p\left(\mathbf{M}_{1:T} \mid \mathbf{Y}_{1:T}, \Phi^i, \Sigma^i, \boldsymbol{\Omega}^*, \beta^{i-1}, \sigma_\nu^{i-1}\right)}{p\left(\mathbf{M}_{1:T} \mid \mathbf{Y}_{1:T}, \Phi^i, \Sigma^i, \boldsymbol{\Omega}^{i-1}, \beta^{i-1}, \sigma_\nu^{i-1}\right)}, 1\right\}$$

3. Draw $\sigma_m^2 \mid \mathbf{Y}_{1:T}, \mathbf{M}_{1:T}, \Omega^{i-1}, \beta_{1:T}^{i-1}, \sigma_m^{i-1}, \sigma_w^{i-1}, \kappa^{i-1}$. Sample σ_m^2 from $IG\left(\bar{s}_1/2, \bar{s}_2/2\right)$, the known conditional posterior distribution associated with σ_m^2.

4. Draw $\beta_{1:T} \mid \mathbf{Y}_{1:T}, \mathbf{M}_{1:T}, \Omega^{i-1}, \beta_{1:T}^{i-1}, \sigma_m^{i-1}, \sigma_w^{i-1}, \kappa^{i-1}$. Conditional on all other parameters, the law of motion forms a linear Gaussian state space system. This step can be carried out using the simulation smoother detailed in Carter & Kohn (1994) or Primiceri (2005).

5. Draw $\sigma_w^2 \mid \mathbf{Y}_{1:T}, \mathbf{M}_{1:T}, \Omega^{i-1}, \beta_{1:T}^{i-1}, \sigma_m^{i-1}, \sigma_w^{i-1}, \kappa^{i-1}$. Sample σ_w^2 from $IG\left(\bar{w}_1/2, \bar{w}_2/2\right)$, the known conditional posterior distribution associated with σ_w^2.

6. Draw $\kappa \mid \mathbf{Y}_{1:T}, \mathbf{M}_{1:T}, \Omega^{i-1}, \beta_{1:T}^{i-1}, \sigma_m^{i-1}, \sigma_w^{i-1}, \kappa^{i-1}$. The scale parameter is sampled with a MH step outlined in Amir-Ahmadi et al. (2020).

A.2 Markov switching

In the case of Markov switching in β_t, we assume that β_t follows a two state Markov process with

$$\begin{aligned} \beta_t &= \beta_{s_t} \\ \Pr(s_t &= i|s_{t-1} = j) = p_{ij} \\ i,j &\in \{1,2\}. \end{aligned}$$

We assume following priors

$$\begin{aligned} p(\beta_{s_t=1}) &\sim N(b_1, V_1). \\ p(\beta_{s_t=2}) &\sim N(b_2, V_2). \\ p_{11} &\sim beta\left(a_{11}, b_{11}\right). \\ p_{22} &\sim beta\left(a_{22}, b_{22}\right). \end{aligned}$$

Algorithm 2. For $i = 1, \ldots, N$. At iteration i. The first 3 steps of the algorithm are the same as Algorithm 1.

4. Draw $\beta_{1:T} \mid \mathbf{Y}_{1:T}, \mathbf{M}_{1:T}, \Omega^{i-1}, \beta_{1:T}^{i-1}, \sigma_m^{i-1}, p_{11}^{i-1}, p_{22}^{i-1}, s_{1:T}^{i-1}$. Sample β_t from $N(\bar{b}_1, \bar{V}_1)$ if $s^{i-1} = 1$ and from $N(\bar{b}_2, \bar{V}_2)$ if $s^{i-1} = 2$. Both are known conditional normal distributions.

5. Draw $p_{11}, p_{22} \mid \mathbf{Y}_{1:T}, \mathbf{M}_{1:T}, \Omega^{i-1}, \beta_{1:T}^{i-1}, \sigma_m^{i-1}, p_{11}^{i-1}, p_{22}^{i-1}, s_{1:T}^{i-1}$. Sample p_{11} from $beta(\bar{a}_{11}, \bar{b}_{11})$ and p_{22} from $beta(\bar{a}_{22}, \bar{b}_{22})$. Both are known conditional beta distributions (see Frühwirth-Schnatter (2006), page 330).

6. Draw $s_{1:T} \mid \mathbf{Y}_{1:T}, \mathbf{M}_{1:T}, \Omega^{i-1}, \beta_{1:T}^{i-1}, \sigma_m^{i-1}, p_{11}^{i-1}, p_{22}^{i-1}, s_{1:T}^{i-1}$. Sample $s_{1:T}$ using the Multi-Move sampler outlined in Frühwirth-Schnatter (2006),

algorithm 11.5.

A.3 More on Priors

We use the benchmark Minnesota prior setting from Giannone et al. (2015) for the VAR with a very loose overall tightness parameter equal to 10. The diagonal elements of the location matrix of the inverse Wishart prior are fixed to estimates based on pre-sample data (lag length). We use fairly uninformative prior for the residual variance $\sigma_m^2 \sim IG(s_1/2, s_2/2)$. For the estimation of the time variation κ, we adopt the half-Cauchy prior with scale parameter θ. The prior hyperparameters are summarized in the following table:

Table 1: TVP Benchmark Prior Hyperparameters

s_1	s_2	b_0	V_0	τ	θ
2	0.2	0	1	2	0.01

In case of Markov Switching, the Minnesota prior specification remains the same, the other prior hyperparameters are summarized in the following table:

Table 2: Markov Switching Benchmark Prior Hyperparameters

s_1	s_2	b_1	V_1	b_2	V_2	a_{11}	b_{11}	a_{22}	b_{22}
2	0.2	0	1	0	1	6	1	6	1

All posterior results are based on $100,000$ draws from the MCMC.

B Additional Figures

C Details on Monte Carlo Exercises

All of our Monte Carlo setups consist of two regimes. Our goal is to match the variance of the instrument for a given regime across specifications. We assume that in the benchmark the monetary policy shocks are $N(0, \sigma_e^2)$ and $\beta = 1$ in one regime and equal 0 in the other. Furthermore, we will assume that in the benchmark the variance of the measurement error v_t is a fixed fraction κ of the variance of the monetary policy shock. Hence we have $Var(v_t) = \kappa\sigma_e^2$.

In our Monte Carlo exercise, we simulate 100 samples of length $T = 250$ each. The variables we use in Monte Carlo exercise are the nominal interest rate, output, inflation, and the monetary policy shock from an estimated Smets-Wouters model. The VAR contains simulated nominal interest rate, output and inflation and the lag length is set to 4. In each of the Monte Carlo repetition (in total 100), posterior results are based on 50.000 MCMC draws. The prior specification is exactly the same as in the empirical estimation.

C.1 Benchmark

The measurement equation and the variance in the two regimes are:

$$m_t = e_t + v_t, Var(m_t) = (1+\kappa)\sigma_e^2 \tag{10}$$

$$m_t = v_t, Var(m_t) = \kappa\sigma_e^2 \tag{11}$$

We set $\sigma_e^2 = 0.2290^2$ equal to the DGP value and $\kappa = 0.25$. For $T = 5, ..., 140$ and $T = 150, ..., 230$, $\beta = 0$. Otherwise, $\beta = 1$. These values are chosen to be comparable to the Gertler-Karadi instrument.

C.2 Stochastic Volatility in the measurement error

We now assume that the measurement error v_t has a variance that switches between regimes with values $\sigma_{v,1}^2$ and $\sigma_{v,2}^2$. The measurement equations are given by:

$$m_t = \overline{\beta} e_t + v_t, Var(m_t) = \overline{\beta}^2 \sigma_e^2 + \sigma_{v,1}^2 \tag{12}$$

$$m_t = \overline{\beta} e_t + v_t, Var(m_t) = \overline{\beta}^2 \sigma_e^2 + \sigma_{v,2}^2 \tag{13}$$

We now need to solve the following two equations:

$$\overline{\beta}^2 \sigma_e^2 + \sigma_{v,1}^2 = (1 + \kappa)\sigma_e^2 \tag{14}$$

$$\overline{\beta}^2 \sigma_e^2 + \sigma_{v,2} = \kappa \sigma_e^2 \tag{15}$$

We actually have three unknowns and two equations here. Since all variances have to be positive, we have additional constraints though. We set $\overline{\beta} = \sqrt{\kappa}$ and $\sigma_{v,2}^2 = 0$. This implies $\sigma_{v,1}^2 = \sigma_e^2$.

We set $\sigma_e^2 = 0.2290^2$ (equal to the DGP value) and $\kappa = 0.25$. For $T = 5, ..., 140$ and $T = 150, ..., 230$, $\sigma_{v,2}^2 = 0$. Otherwise, $\sigma_{v,1}^2 = \sigma_e^2$.

C.3 Stochastic Volatility in e_t

We now assume that the variance in the monetary policy shocks changes, with variances $\sigma_{e,1}^2$ and $\sigma_{e,2}^2$. We also allow the measurement error variance $\tilde{\sigma}_v^2$ and the coefficient $\tilde{\beta}$ to be different than in the other specifications (they are fixed across regimes though). The equations in this MC are given by

$$m_t = \tilde{\beta} e_t + v_t, Var(m_t) = \tilde{\beta}^2 \sigma_{e,1}^2 + \tilde{\sigma}_v^2 \tag{16}$$

$$m_t = \tilde{\beta} e_t + v_t, Var(m_t) = \tilde{\beta}^2 \sigma_{e,2}^2 + \tilde{\sigma}_v^2 \tag{17}$$

The equations we need to solve are:

$$\tilde{\beta}^2 \sigma_{e,1}^2 + \tilde{\sigma}_v^2 = (1+\kappa)\sigma_e^2 \tag{18}$$

$$\tilde{\beta}^2 \sigma_{e,2}^2 + \tilde{\sigma}_v^2 = \kappa\sigma_e^2 \tag{19}$$

We can impose $\tilde{\beta} = 1$ here. One solution would then be to set $\tilde{\sigma}_v^2 = 0$, which implies $\sigma_{e,2}^2 = \kappa\sigma_e^2$ and $\sigma_{e,2}^2 = (1+\kappa)\sigma_e^2$.

We set $\sigma_e^2 = 0.2290^2$ and $\kappa = 0.25$. For $T = 5, ..., 140$ and $T = 150, ..., 230$, $\sigma_{e,2}^2 = \kappa\sigma_e^2$. Otherwise, $\sigma_{e,2}^2 = (1+\kappa)\sigma_e^2$.

D Data Sources

For the US economy, we follow Gertler & Karadi (2015) and obtained industrial production (INDPRO), consumer price index (CPIAUCSL) and 1-year treasury rate (GS1) from FRED (`https://fred.stlouisfed.org/`). The data for the excess bond premium is obtained from Board of Governors (`https://www.federalreserve.gov/econresdata/notes/feds-notes/2016/files/ebp_csv.csv`). The instrument of Gertler & Karadi (2015) is obtained from the replication file of the paper (`https://www.openicpsr.org/openicpsr/project/114082/version/V1/view`). The instrument of Miranda-

Agrippino & Ricco (2022) is obtained from the personal website of Silvia Miranda-Agrippino (http://silviamirandaagrippino.com/s/Instruments_web-x8wr.xlsx). For the UK economy, we use the replication data and instrument of Cesa-Bianchi et al. (2020) from https://github.com/ambropo/MP_HighFrequencyUK/.