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Learning from Errors: The case of monetary and fiscal policy regimes

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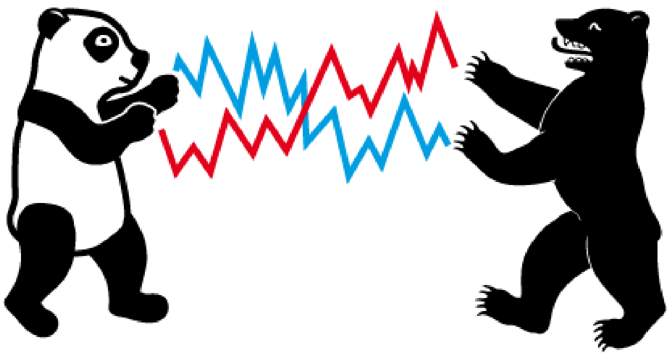

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LEARNING FROM ERRORS:
THE CASE OF MONETARY AND FISCAL POLICY REGIMES

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Abstract. The New Keynesian theory of inflation determination has been under scrutiny due to identification issues, which rather have to do with the mechanism of inflation determination at its core (i.e. Cochrane (2011)). Moreover, similar identification problems arise in the case of fiscal inflation (see for example Leeper and Leith (2016), Leeper and Li (2017) and Leeper and Walker (2012)). This paper makes a positive contribution. We argue that statements about observational equivalence stem from referring to the equilibrium path, while this should not be our primary source of identifying restrictions. Moreover, policy identification (or lack thereof) relies on assumptions on the underlying shock structure, which is unobservable. We instead extract shocks using heterogeneous uncertain restrictions and external datasets, that is, we learn from errors. We are then able to recover deep and policy parameters irrespective of the prevailing equilibrium. We provide time varying evidence on the efficacy of policy in stabilizing the US economy and on the time varying plausibility of Ricardian versus non-Ricardian price determination. Results are work in progress.

JEL Classification: C11, C13, E62, E63

Keywords: Monetary and fiscal policy, Price Determination, Identification, Learning from errors

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1. Introduction

The recent US and European economic depressions have re-ignited academic interest in examining the effectiveness of policy in determining economic activity. In particular, the role of monetary and fiscal policy in determining the price level and inflation are still topics of ongoing research. One of the many reasons for which the academic debate has still not settled down is the host of empirical issues that arise when studying the empirical implications of monetary and fiscal policy interactions, see for example Cochrane (2011) and Leeper and Leith (2016); Leeper and Walker (2012) .

As argued by Cochrane (2011), the New Keynesian monetary theory relies on central banks promising to raise the interest rate more than proportionately to inflation, such that the only non-explosive local solution is one in which inflation jumps with the monetary policy shock. If this theory is a good approximation to the mechanism of inflation determination, which also implies that non-local solutions are ignored, policy rule identification seems almost impossible ; the monetary policy shock is endogenous and no valid instruments exist. Moreover, determinate and indeterminate equilibria are observationally equivalent once we allow for a general autocorrelation structure in the disturbances. With regards to fiscal policy, as argued by Leeper and Leith (2016) and Leeper and Li (2017), autocorrelated fiscal disturbances plague the identification of fiscal policy rules, and this has to do with the forward looking nature of debt valuation. In addition, as shown in Leeper and Walker (2012), one can find specifications of monetary and fiscal rules such that the equilibria under different active/passive policy configurations are observationally equivalent.

Obviously, one cannot understate the importance of these issues, and this calls for efforts to resolve them from a methodological point of view. This paper proposes such a methodology. *First*, we argue that much of the statements on observational equivalence stem from equilibrium reasoning, while the latter cannot be the primary source of identifying restrictions. We should instead rely on information provided by the reduced form and the restrictions arising from the optimal behavior of the private sector.

By utilizing a limited information approach, we avoid the problem of equilibrium selection. This is particularly important as equilibrium selection implies certain parametric restrictions which nevertheless cannot be validated if the equilibria are observationally equivalent. The limited information approach builds on ideas proposed by Fuhrer and Moore (1995) and Cogley and Sbordone (2008) within a different context.

Second, what we described above is still the first best solution, which is actually infeasible, since disturbances are unobserved, and no observed instrument can resolve endogeneity. In fact, the common root of all of the identification problems is the *unobservability* of policy shocks. Our main methodological contribution is to propose a feasible approach, which under conditions can achieve the first best. What is -to the best of our knowledge- new in our methodology is that we recover the unobserved shocks using heterogeneous restrictions and external datasets. This is where "learning from errors" comes from. We treat shocks identified using different uncertain restrictions as observables conditional on parameters. We also add to the set of observables shocks that are identified using other approaches. We then extract a *filtered* shock, which is the factor that best explains all the different imperfect observations. Since these observations are not the result of independent measurement but of independent restrictions, the extracted measure is endogenously determined by the relative validity of the restrictions. We formally show how and under which conditions the heterogeneous information can provide an updated estimate of the shock. A byproduct of this method is that we can also characterize the *plausibility* of each identifying restriction over time.

We deem that this is a pragmatic approach; entertaining multiple identifying restrictions provides an edge to simply adhering to a particular one. What is more is that different papers have suggested and produced different estimates of shocks. As Ramey (2016) concludes after examining many of these approaches, we are indeed closer to understanding the shocks that drive economic fluctuations. Combining this information is therefore a logical step forward.

There is also a deeper reason for which identifying the unobserved policy shocks has to be as theory free as possible, and this has to do with the refutability of the theory itself. The inability to distinguish between different mechanisms of price determination is due to the circular reasoning involved in this endeavor: If we use a particular theory to identify policy shocks, then the corresponding estimates of the systematic component of policy cannot be used to refute the theory itself. Analogously, if identification requires equilibrium selection, then the corresponding estimates cannot refute the chosen regime.

Our empirical contribution is to provide new evidence on the efficacy of policy in stabilizing the US economy over time. Given estimates of fiscal and monetary rules that are not subject to bias coming from equilibrium selection, and estimates of other parameters i.e. the slope of the Phillips curve, we can then judge whether the US has been following active/inactive/indeterminate mix of monetary and fiscal policies over its post WW-II history by looking at the implied determinacy regions of a stylized complete model.

Which model is employed can be important, but given that the parameters governing determinacy are identified without utilizing knowledge of the prevailing equilibrium, we can give a more credible answer to the question of policy effectiveness. Moreover, estimates of fiscal and monetary rules can be used to calibrate elaborate DSGE models that perform conditional analysis e.g. Leeper, Traum, and Walker (2017).

What is also important is the aspect of time variation, as the mechanism of price determination can differ across time. Since all regimes are a priori plausible, it is legitimate to look for evidence of monetary or fiscal determination in relatively short periods of time.

Connections to the literature. This paper is related to different strands of the literature. As we have already mentioned, the paper contributes to the voluminous literature on historical monetary policy analysis and testing for indeterminacy see e.g. Lubik and Schorfheide (2004); Clarida, Gali, and Gertler (1998, 2000); Rotemberg and Woodford (1997); Orphanides (2003) to name a few. Most or all of the past approaches have relied on an a priori restricted shock structure (either in a structural sense or through an exclusion restriction) which has been heavily criticized by Cochrane (2011). Moreover, as most of the literature has focused on local determinacy, we do not consider non-local equilibria i.e. Benhabib, Schmitt-Grohe, and Uribe (2001). Due to the econometric method we use, the effective sample ends in 2011Q4, and the zero lower bound (ZLB hereafter) only appears to bind after this period. Correspondingly, from a retrospective point of view, nobody expected for the ZLB to last so long and thus rational expectations (or perfect foresight) of such a possibility are outside the scope of our effective sample.

Regarding fiscal inflation, much of the theory we will refer to goes back to the work of Leeper (1991); Woodford (1995); Sims (1994); Cochrane (1998). Different authors have criticized the "fiscal theory of the price level", including Buiter (2002); Bassetto (2002); Kocherlakota and Phelan (1999).

Moreover, since we focus on policy regimes, we use the approach of Primiceri (2005) as a starting point. Several papers have studied the stability of monetary policy and other structural relations i.e. Canova and Ferroni (2012); Cogley and Sargent (2001); Sims and Zha (2006). Papers that also estimate monetary and fiscal regimes but use completely specified DSGE models are Gonzalez-Astudillo (2013); Bianchi (2012). In addition, the methodology we propose will utilize shocks identified by other researchers using different approaches. We encourage the reader to refer to Ramey (2016) for a comprehensive summary of the different approaches which we will refer to later on.

Regarding the estimation method, we differ from the VAR-MD approach of Cogley and Sbordone (2008) by obtaining draws for the structural parameters using a pseudo-density induced by a localized GMM criterion[1], in the spirit of Chernozhukov and Hong (2003). Cogley and Sbordone (2008) note that multiple solutions to the mapping between the reduced form and the structural parameters causes convergence problems which prevent them from conducting full Bayesian inference. The multiplicity issue has also been recognized by Kurmann (2007). There is however, a deeper reason for which one cannot conduct Bayesian inference, and this has to do with the fact that there is no joint distribution for the reduced form and structural parameters. Our approach circumvents this issue as we use GMM instead of minimum distance and there is therefore additional randomness even if we condition on the reduced form parameters. We elaborate on this issue in the Appendix.

The rest of the paper is organized as follows. Section 2 gives an example of the identification issue and how the suggested approach can resolve it. Section 3 provides the general methodology and Section 4 presents the preliminary results. Section 5 concludes. The Appendix contains details on the extraneous data used in the extraction of the common shock component and some comments on the limited information approach.

Finally some words on notation. Let $\mathbb{Y} := \{Y_t\}_{t \leqslant T}$ denote the vector of observations where Y_t is a $k \times 1$ vector. We denote by $\mathbb{E}_t(.)$ the conditional expectation with respect to the objective distribution and $\mathbb{E}_{f,t}(.)$ the expectation with respect to the statistical model described by the density $f(Y_t, \varphi)$. Therefore $\varphi \in \Phi$ is the set of reduced form parameters and $\vartheta \in \Theta$ are the corresponding structural parameters of interest. Finally, let Θ_α^{CS} be the corresponding $1 - \alpha$ level confidence set.

[1]Localization is similar to the one used by Giraitis, Kapetanios, Theodoridis, and Yates (2014)

2. Regime Dependent Identification

In this section we revisit the view that identification depends on the type of policy implemented. According to this view, due to the fact that the private sector forms Rational expectations which are based on policy behavior, the resulting equilibrium path makes identification of the policy that actually caused it impossible.

There are at least two types of identification problems that can be caused by policy. The first is failure of empirical identification in the case when policy is successful. Reducing inflation volatility essentially increases the variance of the estimates of the Taylor rule as instruments become weaker (see e.g. Mavroeidis (2010)). The second, which is what we analyze below, is a population identification issue that has to do with observational equivalence across regimes. As we argued in the introduction, we will illustrate that this is actually an unnecessarily pessimistic view and we will show how identification can be easily restored.

2.0.1. ***Example***. Adapting the simple example of Cochrane (2011), the economy is characterized by the Fisher relation and the Taylor rule, whose disturbance is autocorrelated:

$$\begin{aligned} i_t &= r + \mathbb{E}_t \pi_{t+1} \\ i_t &= r + \alpha \pi_t + x_t \\ x_t &= \rho x_{t-1} + \epsilon_t \end{aligned}$$

The equilibrium condition in this economy is therefore:

$$\mathbb{E}_t \pi_{t+1} = \alpha \pi_t + x_t \tag{1}$$

where the interesting case arises when $\alpha > 1$. Under the latter, the only locally bounded solution path is the one in which inflation jumps with the monetary policy shock, $\pi_t = \frac{x_t}{\rho - \alpha}$.

Intuitively, if the central bank behavior implies that inflation will rise indefinitely, the only possible bounded path is the one in which expectations jump immediately to the target. The resulting equilibrium sequences are therefore as follows:

$$\begin{aligned}
\pi_t &= \rho\pi_{t-1} + \frac{\epsilon_t}{\rho - \alpha} = \rho\pi_{t-1} + w_t \\
i_t &= r + \rho\pi_t + x_t
\end{aligned}$$

If identification is based on the equilibrium process, α is unidentified as it disappears from the reduced form likelihood function. Moreover, under indeterminacy, there is a family of paths that satisfy (1), indexed by ξ_t, the sunspot shock : $\pi_t = \alpha\pi_{t-1} + x_{t-1} + \xi_t$. One can readily see that the inflation time series produced by an economy under indeterminacy is indistinguishable from that produced by the determinate economy, for some specification of ξ_t. This is an example of observational equivalence that can occur, and has been the source of controversy about the results of previous studies on the effectiveness of monetary policy throughout US post-war economic history[2].

Nevertheless, this result ignores the fact that the reduced form, that is, the equilibrium process, can be identified from the data. Moreover, since the equilibrium condition (1) holds irrespective of the prevailing equilibrium path, this should be our primary source of identifying restrictions. To maximize clarity, we illustrate how identification can be achieved by combining a reduced form model with the private sector behavioral restrictions.

Suppose we only have data on inflation, for which we write down the following state space model:

$$\begin{aligned}
\begin{pmatrix} \pi_t \\ x_t \end{pmatrix} &= \begin{pmatrix} F_{11} & F_{12} \\ F_{21} & F_{22} \end{pmatrix} \begin{pmatrix} \pi_{t-1} \\ x_{t-1} \end{pmatrix} + \begin{pmatrix} G_1 \\ G_2 \end{pmatrix} w_t \\
\hat{\pi}_t &= \pi_t
\end{aligned}$$

[2]See Cochrane (2011) for an extended discussion on this issue, and references therein.

where $w_t \sim N(0, \sigma_w^2)$. As the state space model is correctly specified, which is something that we can always test against the data, we can use it to both identify x_t and evaluate (1).

The reason for which we can correctly identify x_t is because it is perfectly correlated with π_t. In the Appendix we illustrate how a simple application of the Kalman filter enables us to identify x_t from observations of inflation. What is also true though is that if there was no correlation, then the identification problem goes away, as $\rho = 0$. Using π_t to construct the unconditional moment restriction identifies ϕ as follows: $\hat{\alpha} \to F_{11} - \frac{\mathbb{E}x_t\pi_t}{\mathbb{E}\pi_t^2} \equiv \rho - (\rho - \alpha)$. Suppose now that the true equilibrium process is the indeterminate one i.e. $\pi_t = \alpha\pi_{t-1} + x_{t-1} + \xi_t$. In this case the state space model will produce a noisy measure of x_t, $\hat{x}_{t|t}$, which does not matter. Using again π_t to construct the unconditional moment restriction, $\hat{\alpha} \to F_{11} = \alpha$.

Note that the state space model has been used to motivate how we can identify x_t and how it can be used to compute $\mathbb{E}\pi_{t+1}$ in (1). Other reduced form models can be used, as long as they can be instrumental in identifying a measure of the unobserved shock. Again, since the latter is model dependent, then combining alternative measures is a logical consequence.

3. Methodology

3.1. **Learning from Errors.** Much of the literature on the external identification of shocks has focused on using extraneous information to identify the cumulative effects of monetary policy surprises, with mixed evidence on the effects of these shocks on business cycles. In this paper, as we already argued, we focus on the systematic component of monetary and fiscal policy.

Looking at the restriction implied by condition (1), once we have some estimate of the monetary policy shock, $\hat{x}_t$, estimating ϑ using data on inflation is straightforward. The advantage of using (1) to identify ϑ lies in the fact that we do not impose any equilibrium selection, as both determinate and indeterminate regimes are consistent with (1).

We are not the first to use a proxy for the monetary policy shock to identify policy relevant parameters, see for example Mertens and Ravn (2014), embedded in the Bayesian SVAR framework by Caldara and Herbst (2016). We differ from these approaches in the following ways. First, similar to Caldara and Herbst (2016) and contrary to Mertens and Ravn (2014), we embed the external information in a likelihood framework. Contrary to Caldara and Herbst (2016), we do not use this information to inform the choice of structural specification, as we simply do not adhere to a specific one. In fact, we use many plausible structural specifications to learn about the unobserved shock (there is an infinite number of them!).

Our methodology only requires being able to obtain preliminary estimates of shocks and together with other proxies to filter out the underlying unobserved shock. Since we aim to do this for all policy shocks, we focus on filtering out tax, government spending and monetary policy states. There is a certain degree of freedom in which model to use to extract the unobserved component. For our current results we have used a Bayesian factor model. Let Y_t be the set of variables included in the reduced form VAR, which has the following form:

$$y_t' = x_t' B_{1,t} + \epsilon_t' \tag{2}$$

The innovations ϵ_t are linear combinations of underlying shocks, whether fundamental or not, and thus satisfy $\epsilon_t = C\Sigma_{u,c} u_t$ where $u_t \sim N(0, I_{n_u})$ and $\Sigma_{u,c}\Sigma_{u,c}' = \Sigma_u$. Denoting the set of proxies to the underlying shocks by $\tilde{u}_t$, and η_t the vector of measurement errors with variance Σ_η, we assume the following link function:

$$\tilde{u}_t' = u_t' \boldsymbol{\lambda} + \eta_t' \tag{3}$$

Given that $(B, C\Sigma_u C')$ are identified from the autocovariances of Y_t, we turn the problem of identifying u_t on its head by recognizing that there exist many combinations of C and Σ_u that give rise to the same tuple $(B, C\Sigma_u C')$ but produce different sequences of $\hat{u}_t$.

Letting $Q := C\Sigma_{u,c}$, we denote by $\mathcal{U}^{\mathcal{Q}}$ the set of all sequences $\{\hat{u}_t\}^q$ for $q : q \in \mathcal{O}_{n_e}$. While we have point identification of the reduced from, in contrast to the partially identified SVAR, the class of identified sequences of $\mathcal{U}_t^q$ is indexed by a class of matrices Q which has zero measure, (unless we impose sign restrictions). The most popular class of matrices is that when the order of the variables in the VAR changes and a standard Cholesky identification scheme is used. This is equivalent to choosing a particular permutation matrix C. Obviously, other assumptions on C i.e. other zero or non zero restrictions can also be considered, as long as they make economic sense.

Once we have generated alternative sequence of u's, we can then estimate a standard model of unobserved components, i.e. a factor model. More particularly, by combining (2) and (3), we can define a state space model where the states are the shocks themselves, while the set of of observables are defined by $Z_t \equiv (\mathcal{U}_t^Q, \tilde{u}_t)$ where $\tilde{u}_t$ are externally identified shocks :

$$u_t = \Gamma u_{t-1} + v_t \tag{4}$$

$$\begin{pmatrix} \hat{u}_t'^{q_1} \\ \hat{u}_t'^{q_2} \\ \vdots \\ \hat{u}_t'^{q_N} \\ \tilde{u}_t' \end{pmatrix} = \Lambda u_t + \eta_t \tag{5}$$

where Γ is diagonal and Λ subject to zero restrictions to guarantee identification.

3.2. **How can we learn?** To maximize clarity, we distinguish between what can be learned from identification errors, $\mathcal{U}_t^Q$, and external information, $\tilde{u}_t$. Naturally, this depends on the structure of Λ_t and the relative magnitude of the respective measurement error. We first analyze the case of $\mathcal{U}_t^Q$, which is a novel contribution of this paper. Every element of $\mathcal{U}_t^Q$ can be though as an *uncertain identifying restriction* in the form of $u_t^{q_i} = B_{q_i}^{-1} B u_t$, where B contains the prevailing cross equation restrictions in the economy. Without loss of generality, we represent $vec(B_{q_i})$ as the closest (in Euclidean distance) vector γ to $vec(B)$ subject to restriction $\underset{n^2 \times k}{\delta_i} \gamma = b_i$. Letting $\underset{k \times k}{\mathcal{Q}_i}$ and $\underset{k \times k}{R_i}$ denote the orthogonal and upper triangular matrices arising from the QR decomposition of $\delta_i' \delta_i$, the $\gamma^\star := vec(B_{q_i}) = vec(B) - \delta_i' R_i^{-1} \mathcal{Q}_i' (\delta_i vec(B) - b_i)$.

After some algebra, Λ_{q_i}, which is the subcomponent of Λ in (5) that links $u_t^{q_i}$ to u_t will have the following structure:

$$vec(\Lambda_{q_i}) \quad = \quad vec(I_N) - (B'^{-1} \otimes I_N) \delta_i' R_i^{-1} \mathcal{Q}_i' (\delta_i vec(B) - b_i) \tag{6}$$

The above representation is the infeasible case, that is, it can only be computed when B is known. Nevertheless, it is informative in two ways. First, one can use (6) to guide construction of priors for Λ_{q_i}. Since $vec(\Lambda_{q_i})$ is a deterministic function of $(B, \boldsymbol{\delta}, \mathbf{b})$, the only source of uncertainty comes from uncertainty about $(\boldsymbol{\delta}, \mathbf{b})$. As can be readily seen, if restriction i holds, or it is not overidentifying, then the second term vanishes. Therefore, priors that are centered tightly around $vec(I_N)$ necessitate the belief that restriction i is approximately true, or non verifiable. A diffuse prior reflects that the researcher is agnostic about the plausibility of restriction i. Identical priors for restrictions i and j imply the belief that they are approximately similar.

More interestingly, the posterior distribution of $vec(\Lambda_{q_i})$ can only be updated in two ways. If no additional data is used i.e. external measures of shocks, the posterior mean will be determined by the prior weight the econometrician assigns to each $u_t^{q_i}$. This prior weight will only by updated if the restrictions are overidentifying, and the update will depend on the magnitude of $(\delta_i vec(B) - b_i)$. Conversely, if additional data is used, then $vec(\Lambda_{q_i})$ will also be updated through the additional observations. In either case, we can extract a single factor, which is the best estimate of $\left\{u_{t|t}\right\}_{t\leqslant T}$. The more plausible the identifying restriction i, the higher weight the estimate will place on $u_t^{q_i}$.

To show this formally, consider the case when $\Gamma = 0$, that is, we ignore the autocorrelation in the shocks, which leads to a static factor model:

$$\hat{U}_t^q = \Lambda u_t + \eta_t \tag{7}$$

where $\eta_t \sim N(0, \Sigma_\eta)$, and the prior distribution for the loadings is $\lambda \sim N(\mu, C_0)$. Adapting the results of Lopes and West (2004) to the case of one factor, which implies that Λ will be a vector[3], the posterior $p(\Lambda_{q_i})$ will be Normal with mean m_i and variance C_i where

$$m_i = C_i(C_0\mu_i + \sigma_i^{-2}u'\hat{u}_i^q) \tag{8}$$

$$C_i^{-1} = C_0^{-1} + \sigma_i^{-2}u'u \tag{9}$$

and σ_i^{-2} is the posterior variance of η_t. As evident, the posterior mean and variance will be updated by the data through $\hat{u}_i^q$ directly and through u indirectly, while $(\mu_i, C_{0,i})$ will reflect prior beliefs. By definition, $u'\hat{u}_i^q = u'SB_{q_i}^{-1}B\boldsymbol{u}$ where S is a matrix that selects shock u. Under exact identification, $SB_{q_i}^{-1}B_{q_i}'^{-1}S' = SB^{-1}B'^{-1}S'$ and therefore $S\boldsymbol{\Lambda}B^{-1}B'^{-1}\boldsymbol{\Lambda}'S' = SB^{-1}B'^{-1}S'$ which implies that $\boldsymbol{\Lambda} = I_{n_u}$ and $\Lambda_{q_i} = 1$ and thus $u'\hat{u}_i^q = u'u$. Under over-identification, the above equality does not hold, and $u'\hat{u}_i^q < u'u$ will reflect how far $(\delta_i vec(B) - b_i)$ is from zero. If the magnitude is large, then Λ_{q_i} will have a lower posterior mean.

Having discussed the relative merits of combining information from different sources, we describe below the full algorithm.

[3]This implies selecting just one shock, that is, a row of $u_t^{q_i} = B_{q_i}^{-1}Bu_t$

3.3. **The Algorithm.** In this section we give a complete description of the algorithm, which only requires the use of standard posterior samplers. Using the fact that conditioning on $(\boldsymbol{Y}, \boldsymbol{X})$, $(\hat{\boldsymbol{U}}, \hat{\boldsymbol{\epsilon}})$ is redundant information for the reduced form parameters of the VAR, and correspondingly, conditioning on $(\boldsymbol{U})$ makes $(\boldsymbol{Y}, \boldsymbol{X}, B, \Sigma_u)$ redundant for the posterior distribution of the rest of the parameters, the posterior distribution of $(B, \Sigma_u, \Gamma, \Lambda, \Sigma_v, \Sigma_\eta)$ can be factorized as follows:

$$p(B, \Sigma_u, \Gamma, \Lambda, \Sigma_v, \Sigma_\eta | \boldsymbol{Y}, \boldsymbol{X}, \hat{\boldsymbol{U}}, \hat{\boldsymbol{\epsilon}}) \quad = \quad p(B, \Sigma_u | \boldsymbol{Y}, \boldsymbol{X}) p(\Gamma, \Lambda, \Sigma_v, \Sigma_\eta | \hat{\boldsymbol{U}}, \hat{\boldsymbol{\epsilon}})$$

Given standard priors $\pi(B, \Sigma_u)$ i.e. Normal - Wishart or the Minessota prior, we can draw (B^j, Σ^j), and then given the latter and a draw of Q^j from $\pi(Q)$ we can construct $\boldsymbol{U}^{Q,j}$. Given $\boldsymbol{U}^{Q,j}$ and proxy variables $\hat{\epsilon}$, we can obtain $(\Gamma^j, \Lambda^j, \Sigma_v^j, \Sigma_\eta^j)$ using a Metropolis step in the case of state space formulation of (5) or another Gibbs step if a Bayesian factor model is utilized.

The above algorithm would be complete if one was interested in estimates of the shocks per se. In the next section we describe how draws from $p(B, \Sigma_u, \Gamma, \Lambda, \Sigma_v, \Sigma_\eta | \boldsymbol{Y}, \boldsymbol{X}, \hat{\boldsymbol{U}}, \hat{\boldsymbol{\epsilon}})$ can be used as inputs for an additional step, that of obtaining draws from $p(\vartheta | \boldsymbol{Y}, \boldsymbol{X}, \hat{\boldsymbol{U}}, \hat{\boldsymbol{\epsilon}})$, the quantity of interest. As we explain in the Appendix, since ϑ does not enter the likelihood function, we can use a Metropolis - Hastings step (or several) to draw ϑ_j's as follows:

$$\begin{aligned}
\mu(\vartheta, \phi | \boldsymbol{X}) &= \mu(\vartheta | \phi, \boldsymbol{X}) \mu(\phi | \boldsymbol{X}) \\
&= \mu(\vartheta | \phi) l(\boldsymbol{X} | \phi) \pi(\phi) \\
&\propto e^{\left(-T \mathbb{E}_f(m(X_t, X_{t-1}, \vartheta))' V_m^{-1} \mathbb{E}_f(m(X_t, X_{t-1}, \vartheta)\right)} l(\boldsymbol{X} | \phi) \pi(\phi)
\end{aligned}$$

where $V_m^{-1} := \mathbb{E}_f(m(X_t, X_{t-1}, \vartheta) m(X_t, X_{t-1}, \vartheta)')$. It is crucial to note that the above algorithm is almost the same when there exists time variation in both B and Σ_{uc}. Since we only want to extract time variation in the reduced from parameters, standard algorithms like Carter and Kohn (1994) as implemented by Primiceri (2005) can be readily used. Given $\{\hat{B}_t\}_{t\leqslant T}$ and $\{\hat{\Sigma}_{uc,t}\}_{t\leqslant T}$, the rest of the algorithm is the same.

To obtain the corresponding time varying structural parameters ϑ_t, we exploit the fact that each economic condition is a conditional moment equality. Since we compute conditional moments using the model i.e. $f(X_{t+1}|X_t, \hat{B}_t, \Sigma_t)$, this amounts to a restriction $R_{X_{t-1}}(\varphi, \vartheta) = 0$, which obviously holds for all X_{t-1}. We thus employ local averaging using weights $\mathcal{K}_{l,t}$, i.e. the local GMM criterion uses the following moment condition:

$$\sum_{l=\underline{l}}^{\bar{l}} \tilde{\mathcal{K}}_{l,t} \mathbb{E}_{f(B_t,\Sigma_t;X_l)} m(X_t, X_{t-l}, \vartheta) \quad = \quad 0 \tag{10}$$

where $\tilde{\mathcal{K}}_{l,t} := \frac{\mathcal{K}_{l,t}}{\sum_l \mathcal{K}_{l,t}}$ and $(\underline{l}, \bar{l})$ is the range of observations around data point t. We use $\tilde{\mathcal{K}}_{l,t} \propto N(l, h)$ where h is the bandwidth i.e. the closer l is to t, the more information X_l has about X_t. The use of local averaging to obtain time varying estimates has been recently proposed by Giraitis, Kapetanios, and Yates (2014) in the context of time varying autoregressive models, while Petrova (2018) applies local averaging to the same class of models using a quasi-Bayesian local likelihood.

4. Empirical Application

4.1. **A conventional macroeconomic model.** To characterize the alternative regimes, we utilize a model along the lines of Woodford (1995), where we allow for the possibility of alternative fiscal - monetary regimes. We differ from Woodford (1995) by letting government spending be wasteful i.e. the utility of the representative household does not depend on G and fiscal policy is determined by a simple rule. To generate demand for money balances, we allow for money in the utility function. Nevertheless, money demand will not have any effect on which equilibrium regime will occur, so we will not identify the relevant parameters i.e. the inverse elasticity of inter-temporal substitution for money balances, χ. Since the model is otherwise standard, we present below the log-linearized equilibrium conditions:

$$\hat{c}_t = \mathbb{E}_t\hat{c}_{t+1} - \frac{1}{\sigma}\left(i_t - \mathbb{E}\pi_{t+1}\right) \tag{11}$$

$$\hat{\pi}_t = \beta\mathbb{E}_t\hat{\pi}_{t+1} + \kappa\hat{y}_t \tag{12}$$

$$\hat{m}_t = \chi\left(\frac{1}{\sigma}\hat{c}_t - \frac{\beta}{1-\beta}\hat{i}_t\right) \tag{13}$$

$$\hat{b}_t = i_t + \frac{1}{\beta}(\hat{b}_t - \hat{\pi}_t) + (\frac{1}{\beta} - 1)\hat{s}_t - \gamma(\hat{m}_t - \hat{m}_{t-1} + \hat{\pi}_t) \tag{14}$$

$$\hat{s}_t = \xi_s\hat{b}_{t-1} + \epsilon_{s,t} \tag{15}$$

$$\epsilon_{s,t} = \rho_s\epsilon_{s,t-1} + u_{s,t} \tag{16}$$

$$\hat{i}_t = \phi_\pi\hat{\pi}_t + \phi_Y\hat{y}_t + \epsilon_{i,t} \tag{17}$$

$$\epsilon_{i,t} = \rho_i\epsilon_{i,t-1} + u_{i,t} \tag{18}$$

Letting $X_t := (\hat{\pi}_t, \hat{y}_t, \epsilon_{i,t}, \hat{m}_{t-1}, \hat{\hat{b}}_t, \epsilon_{s,t})'$ where $\hat{b}_{t-1} := \hat{\hat{b}}_t$ and casting the system in the form $\mathbb{E}_tX_{t+1} = CX_t$ we notice the following two facts: First, C has a lower triangular form, and therefore its eigenvalues will be determined by the eigenvalues of the diagonal blocks that correspond to $X_{1,t} := (\hat{\pi}_t, \hat{y}_t, \epsilon_{i,t}, \hat{m}_{t-1})'$ and $X_{2,t} := (b_t, \hat{\hat{b}}_t, \epsilon_{s,t})'$[4], the monetary block and the fiscal block respectively. The fiscal block has two stable and two unstable

[4] It turns out that whether we choose $X_{1,t} := (\hat{\pi}_t, \hat{y}_t, \epsilon_{i,t}, \hat{m}_{t-1})'$ or $X_{1,t} := (\hat{\pi}_t, \hat{y}_t, \epsilon_{i,t})'$does not matter for determining which regime occurs.

eigenvalues if $\xi \leqslant 1$, or three stable eigenvalues and one unstable if $\xi > 1$. In words, if the fiscal authority responds strongly enough to past innovations to debt, then debt is stabilized while inflation is determined by the monetary block. Correspondingly, and independently of the fiscal stance, the monetary block can have three stable eigenvalues and one unstable if $-1 - \frac{1+\beta}{\kappa}\phi_y - \frac{2(1+\beta)}{\kappa\sigma} < \phi_\pi < 1 - \frac{1-\beta}{\kappa}\phi_y$ or two stable and two unstable eigenvalues if $\phi_\pi > 1 - \frac{1-\beta}{\kappa}\phi_y$ or $\phi_\pi < -1 - \frac{1+\beta}{\kappa}\phi_y - \frac{2(1+\beta)}{\kappa\sigma}$. In the latter case monetary policy is active, and the monetary block pins down inflation. What is more important is that the possibility of regimes only depends on $(\sigma, \beta, \kappa, \phi_\pi, \phi_y)$, which we identify using our methodology.

4.2. **Data and Moment Conditions.** We apply our methodology to estimate simple fiscal and monetary policy rules over the US Post-WWII history. Our initial sample starts from 1948Q1 and ends in 2016Q4. We use the 40 initial observations as a training sample for the TVP-VAR and 20 observations from the beginning and end of the sample to compute the localized GMM criterion and avoid end of sample issues. We thus effectively obtain estimates from 1963Q1 to 2011Q4. We use a seven variable VAR(1) as the benchmark model, with observables constructed as in Leeper and Li (2017). More particularly, we use real Net Taxes (T_t), real Government expenditure (G_t), real GDP (Y_t), Inflation (GDP delflator, π_t) , Federal Funds rate (i_t) and Government Liabilities to GDP (B_t). Conditional on estimates of the shocks, we estimate a forward looking Phillips curve, a forward looking Euler Equation with output and simple Fiscal and monetary policy rules as follows:

$$\pi_t = \beta \mathbb{E}_{f,t}\pi_{t+1} + \kappa y_t \tag{19}$$

$$Y_t = \mathbb{E}_{f,t}Y_{t+1} - \frac{1}{\sigma}\mathbb{E}_{f,t}(i_t - \mathbb{E}_{f,t}\pi_{t+1}) \tag{20}$$

$$i_t = \phi_\pi \pi_t + \phi_Y y_t + \epsilon_{f,i,t} \tag{21}$$

$$T_t - G_t = \xi_s B_{t-1} + \epsilon_{f,T,t} - \epsilon_{f,G,t} \tag{22}$$

$$B_{t+1} = i_t + \beta^{-1}(B_t - \pi_t) + (\beta^{-1} - 1)(T_t - G_t) - \gamma(M_t - M_{t-1} + \pi_t) \tag{23}$$

where subscript f indicates quantities that are conditional on the VAR.

4.3. **Preliminary results.** In Figure 1 we plot the pointwise 84% credible sets for each parameter over the period 1963Q1 to 2011Q4. In Figure 2, we plot the probability of observing each policy regime which is computed as the proportion of posterior draws that lie in the subset of the parameter space that is relevant for each regime.

Moreover, in Figure 3 we plot median measures of the inverse $J-$ statistics computed at each point in time. These $J-$ statistics are the outcome of the two different sets of overidentifying restrictions used in the estimation. The first restriction is a $Blanchard-Perotti$ restriction which allows contemporaneous feedback from debt to surpluses and contemporaneous effects of the monetary policy shock to inflation and vice versa, which we coin as *Ricardian*. The second identifying restriction is a $Blanchard-Perotti$ type of restriction which does not allow for contemporaneous feedback from debt to surpluses while it allows for contemporaneous effects of the monetary policy shock to inflation. We coin the opposite case as *Non-Ricardian*. Since the two identifying restrictions differ only in allowing for contemporaneous effects of debt or not, and since we do not weight the elements of B in different ways, we expect that the difference is due to the Ricardian versus Non-Ricardian distinction. Note that both of the restrictions are overidentifying by one degree.

Our preliminary results show that up to 1990 active fiscal - passive monetary policy has been the most probable regime, while indeterminacy receives roughly 30% probability. During the last years of the "Great Moderation", that is, from mid 1990's to mid 2000's there is no evidence for a very likely regime, although active monetary - passive fiscal policy receives a probability of $30\% - 40\%$. Finally, from mid 2000's, indeterminacy and active fiscal-passive monetary policy are equally plausible.

5. Conclusion

Thia paper proposes a feasible approach to identify time variation in monetary and policy rules without taking a stance on which regime is active at each point in time. This is particularly important as regimes are a priori observationally equivalent. We argue that observational equivalence has to do with the unobservability of shocks. We deal with the latter by employing heterogeneous uncertain restrictions, which can then be used to extract estimates of shocks that, by design, are belief free. This implies that regimes are no longer observationally equivalent. We apply the methodology to the US economy. Results are still work in progress.

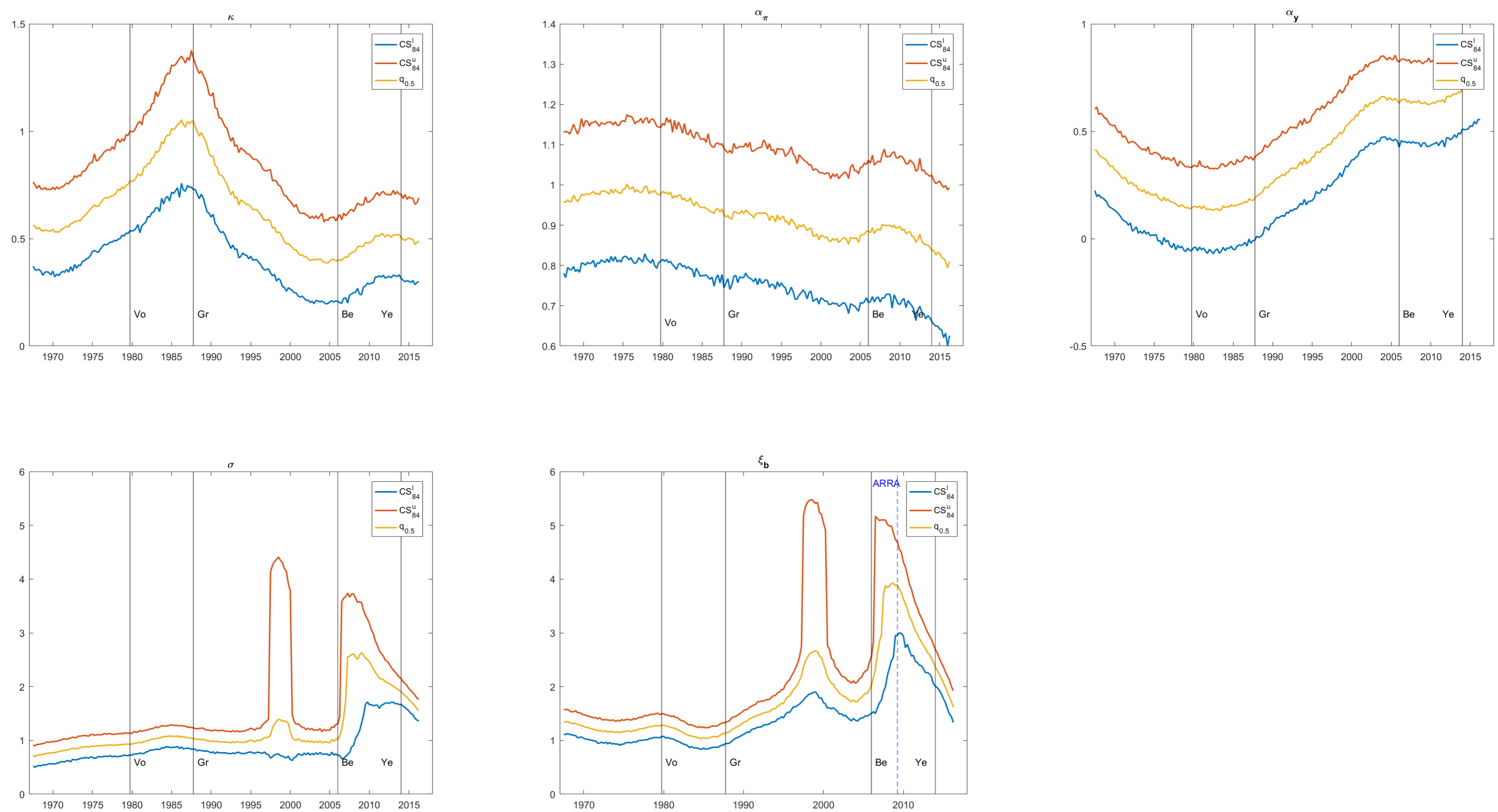

FIGURE 1. Time Varying Structural Parameters

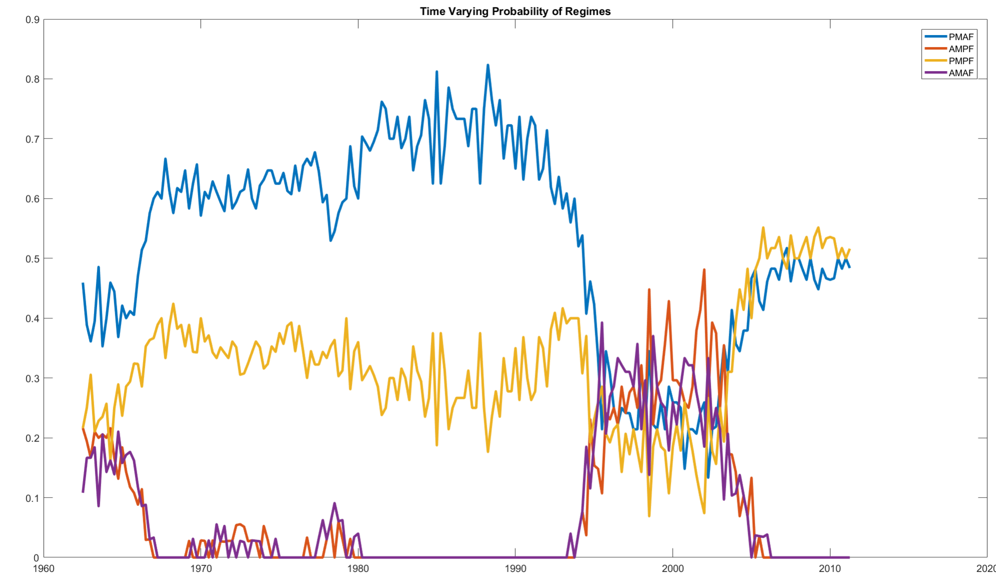

FIGURE 2. Time Varying Regimes

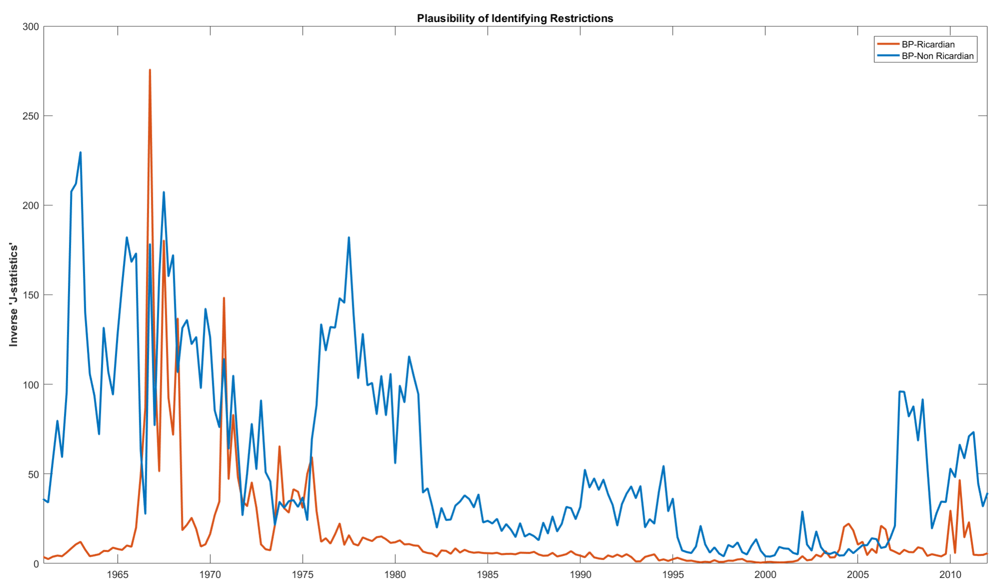

FIGURE 3. Plausibility of Identifying Restrictions

6. Appendix

6.1. **Identifying x_t from π_t in Example.** Recall that in the determinate equilibrium, inflation jumps with the monetary policy shock i.e. $\pi_t = \frac{\xi_t}{\rho-\alpha}$. This results into the following system:

$$\begin{aligned}\begin{pmatrix}\pi_t \\ x_t\end{pmatrix} &= \begin{pmatrix}\rho & 0 \\ 0 & \rho\end{pmatrix}\begin{pmatrix}\pi_{t-1} \\ x_{t-1}\end{pmatrix} + \begin{pmatrix}\frac{1}{\rho-\alpha} \\ 1\end{pmatrix}\epsilon_t \\ \hat{\pi}_t &= \pi_t\end{aligned}$$

Let $s_t \equiv (\pi_t, x_t)'$ and define by $s_{t,t}$ the updated value for s_t and $s_{t+1,t}$ the one step ahead prediction. Correspondingly, define $\Omega_{t,t}$ and $\Omega_{t+1,t}$ as the updated and one step ahead variance of s_t. Moreover, let $\Sigma_{t+1,t}$ be the forecast error variance for π_t. Substituting for the model, we get the following expressions for each of the above components of the standard Kalman filter recursion:

$$\Omega_{t,t} = \Omega_{t,t-1} - \Omega_{t,t-1}(1,0)'\Sigma^{-1}_{t,t-1}(1,0)\Omega_{t,t-1} = \begin{pmatrix}0 & 0 \\ 0 & \Omega^{22}_{t,t-1} - (\Omega^{11}_{t,t-1})^{-1}\Omega^{21}_{t,t-1}\Omega^{12}_{t,t-1}\end{pmatrix}$$

$$\begin{aligned}\Omega_{t+1,t} &= \begin{pmatrix}\rho & 0 \\ 0 & \rho\end{pmatrix}\Omega_{t,t}\begin{pmatrix}\rho & 0 \\ 0 & \rho\end{pmatrix} + \begin{pmatrix}\frac{\sigma^2}{(\rho-\alpha)^2} & \frac{\sigma^2}{(\rho-\alpha)} \\ \frac{\sigma^2}{(\rho-\alpha)} & \sigma^2\end{pmatrix} \\ &= \begin{pmatrix}\frac{\sigma^2}{(\rho-\alpha)^2} & \frac{\sigma^2}{(\rho-\alpha)} \\ \frac{\sigma^2}{(\rho-\alpha)} & \sigma^2 + \rho^2(\Omega^{22}_{t,t-1} - (\Omega^{11}_{t,t-1})^{-1}\Omega^{21}_{t,t-1}\Omega^{12}_{t,t-1})\end{pmatrix}\end{aligned}$$

and therefore,

$$\begin{pmatrix}\pi_{t,t} \\ x_{t,t}\end{pmatrix} = \begin{pmatrix}\pi_{t,t-1} \\ x_{t,t-1}\end{pmatrix} + \Omega_{t,t-1}(1,0)'\Sigma^{-1}_{t,t-1}(\pi_t - \pi_{t,t-1}) = \begin{pmatrix}\pi_t \\ \rho x_{t-1,t-1} + \frac{(\Omega^{11}_{t,t-1})^{-1}\Omega^{21}_{t,t-1}\epsilon_t}{\rho-\alpha}\end{pmatrix}$$

Substituting for $\Omega^{21}_{t,t-1}$ and $\Omega^{11}_{t,t-1}$, we have that

$$\begin{pmatrix}\pi_{t,t} \\ x_{t,t}\end{pmatrix} = \begin{pmatrix}\pi_t \\ \rho x_{t-1,t-1} + \epsilon_t\end{pmatrix}$$

If we start from an initial value for s_0 i.e. the unconditional mean, while inflation is perfectly observed, the effect of the initial value for identifying x_t will be present for only the first n_1 iterations of the Kalman filter. For $t > n_1$, $x_{t-1,t-1} \approx x_{t-1}$ and thus $x_{t,t} \approx x_t$. The filter usually arrives at this state very fast.

6.2. **VAR and GMM Dataset.** We follow Leeper and Li (2016) in constructing Net Federal Taxes, Spending and Federal Debt.

- Nominal Gross Domestic Product (Y_t^{nom}), Source: U.S. Bureau of Economic Analysis, Table 1.1.5.
- Inflation $\pi_t = \frac{p_t - p_{t-1}}{p_{t-1}}$ where p_t is the Gross Domestic Product Implicit Price Deflator. Source: U.S. Bureau of Economic Analysis, Table 1.1.5. We construct real quantities using the latter.
- Nominal Net Taxes (T) = Federal Taxes (line 2 NIPA 3.2) + Social Insurance contributions (line 11 NIPA 3.2) - Net Transfers
  - Net Transfers = Net current transfers + Net capital transfers and subsidies (line 32 in NIPA Table 3.2) - (Income receipts on assets (line 12 in NIPA Table 3.2) + Current surplus of government enterprises (line 19 in NIPA Table 3.2)).
  - Net current transfers = Current transfer payments(line 22 in NIPA Table 3.2) - Current transfer receipts (line 16 in NIPA Table 3.2).
  - Net capital transfers = Capital transfer payments (line 43 in NIPA Table3.2) - Capital transfer receipts (line 39 in NIPA Table 3.2).
- Nominal Spending = Federal Consumption expenditure (line 20 in NIPA Table 3.2) + Gross government investment (line 42 in NIPA Table 3.2) and Net purchases of non produced assets (line 44 in NIPA Table 3.2) - Consumption of fixed capital (line 45 in NIPA Table 3.2).
- Nominal Federal debt: Using the Government budget constraint $V_t - V_{t-1} = NB_t?S_t$ where seigniorage (S_t) is ΔM_t.
  - Nominal net borrowing (NB): Government Spending + Interest payments (line 29 in NIPATable 3.2) + Nominal Net Transfers - Net Taxes. To construct V_t from 1947:2 we set the value of 1947:1 as in Leeper and Li (2016).
- Monetary base (M_t): Source: St. Louis adjusted monetary base .

- i_t : Federal Funds Rate
- Credit spreads: Moody's Seasoned Baa Corporate Bond Minus Federal Funds Rate, Percent, Quarterly, Not Seasonally Adjusted

6.3. **External Data.** We currently utilize the following extraneous data (that is, data not utilized in the estimation of the TVP-VAR), which do not necessarily exhaust all the identification approaches used up to now, but are available through V. Ramey's website <http://econweb.ucsd.edu/~vramey/research.html#data> and are discussed in her handbook Chapter (Ramey (2016)). Below is a list of the papers and a brief description of the identified shocks:

(1) Narrative - News about military government spending - Narrative (Ramey and Shapiro (1998))

(2) Defense spending: 5 year horizon maximum forecast error variance (Ben Zeev and Pappa (2015))

(3) Tax expectations (Leeper, Richter, and Walker (2012))

(4) Narrative - Exogenous tax changes (Romer and Romer (2010))

(5) Unanticipated Tax changes based on Romer and Romer (2009) Narrative, Mertens and Ravn (2012)

(6) Narrative -Monetary policy shock, Romer and Romer (2004)

Note that news shocks over different horizons are used to partial out their effect from the filtered shocks. Apart from these shocks, we also regress the filtered shocks on a measure of credit spreads (Moody's seasoned Baa corporate bond yield), to partial out the possible endogeneity of the identified shocks to developments in the financial sector as we do not include credit shocks in our baseline specification. This is also related to the work of Caldara and Herbst (2016) who find that including a measure of credit spreads is important.

6.4. **Bayesian Inference and Incomplete Models.** There are several ways to conduct Bayesian inference for structural parameters ϑ when a model is incomplete. Model incompleteness implies that while there is an underlying and possibly time varying mapping between ϑ and ϕ, this mapping is unknown in general, or can be possibly learned using observations. One way to learn about ϑ is to use the underlying moment conditions implied by economic theory.

Assuming a rectangular prior distribution on (φ, ϑ), $\pi(\varphi, \vartheta)$, conditional moments imply the following set of restrictions on the joint conditional posterior distribution $\mu_X(\varphi, \vartheta)$:

$$\int m(X_t, X_{t-1}, \vartheta) f(X_t|X_{t-1}, \phi) dX_t = 0 \tag{24}$$

$$R_{X_{t-1}}(\varphi, \vartheta) = 0 \tag{25}$$

If this restriction holds for all $(X_{t-1}, \varphi) \in \mathcal{X} \times \Phi$, it should also hold for $\pi(\varphi, \vartheta)$, as in Gallant (2016). Therefore, there is singularity in the joint distribution of $\pi(\varphi, \vartheta)$, as the manifold defined by $\bar{R}(\varphi, \vartheta) = 0$ has measure zero under point identification[5].

In order to conduct Bayesian inference for ϑ, the dominant approach is to impose the restrictions directly on $f(X_t|X_{t-1}, \varphi)$ by solving for the equilibrium law of motion, or more generally, to draw directly from the restricted density $f(X_t| \{X_{t-1}, \varphi\} : R_{X_{t-1}}(\varphi, \vartheta) = 0)$, as long as R is invertible in ϑ.

Nevertheless, the way restrictions like $R_{X_{t-1}}(\varphi, \vartheta)$ are imposed matters for economic inference. For example, solving for the model usually requires equilibrium selection, something that can be arbitrary. There are two alternative ways to utilize restriction $R_{X_{t-1}}(\varphi, \vartheta)$. The first is the method by Chernozhukov and Hong (2003) which is quasi Bayesian in

[5]Singularity can hold at various points, depending on whether there is a unique ϑ that satisfies the restriction

nature, and produces valid inference for ϑ by drawing from a pseudo-density defined by an exponentiated GMM type of criterion function. The second, it to utilize the knowledge of $f(X_t|X_{t-1}, \varphi)$ and identify ϑ by solving 13. as a function of (φ, X_{t-1}) or φ in the unconditional case. An advantage of the latter approach is that the posterior distribution of ϑ, $\mu(\vartheta|\boldsymbol{X})$, can be computed by a change of variables. If simulation is involved, then the conditional posterior $\mu(\vartheta|\varphi, \boldsymbol{X})$ exists as the relation between ϑ and φ is now random for finite simulation size. The conditional posterior also exists when the conditional moment restrictions are used which requires local averaging, and therefore additional randomness.

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