SEPARATE CALVO PRICE-STICKINESS PARAMETERS
IN AN AGGREGATE SUPPLY AND DEMAND MODEL

by

ERIC LEVERETT PERKERSON

(Under the direction of Professor George Selgin)

ABSTRACT

I test whether or not the degree of price-stickiness following supply and demand shocks differs. First, I use an aggregate supply and demand model to derive theoretical impulse response functions for both supply and demand shocks. Then, using various identification schemes, I identify supply and demand shocks in monthly time series data of industrial production and the consumer price index from January 1975 to January 2000, which I then use to derive empirical impulse response functions corresponding to the two shocks. I then estimate the Calvo price-stickiness parameter separately for supply and demand shocks by separately fitting the theoretical impulse response functions to the different empirical ones. I find that there is no significant improvement in the fit of the theoretical impulse response functions to the empirical impulse response functions by estimating the Calvo parameter separately for supply and demand shocks, and the evidence suggests that firms take approximately the same amount of time to adjust prices in response to demand shocks as they do to supply shocks.

INDEX WORDS: Calvo model, price-stickiness, supply and demand, Blanchard-Quah decomposition
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in an Aggregate Supply and Demand Model

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1. Introduction

A popular way of modeling price stickiness is the one developed by Calvo (1983), which models price stickiness by preventing a fixed portion of firms from changing their prices in a given period, meanwhile allowing all other firms to change their prices. This fixed portion, called the Calvo price-stickiness parameter or simply Calvo parameter, is not, however, a “deep” parameter. That is to say the Calvo parameter is an instrument introduced to make modeling price stickiness tractable, and because of its formulation lacks a realistic microeconomic foundation. The Calvo parameter does not represent some underlying trait about how firms change their prices in the real world.

In particular, the Calvo model assumes that firms will adjust their prices in response to supply shocks in the same fashion as they adjust their prices in response to demand shocks. There are in fact good reasons for why these responses should be different. Firms may be prevented from changing their prices quickly in response to a demand shock, either because of the difficulty of identifying the change or by the pressure put on firms by customers to keep prices stable (Okun 1981). Additionally, monetary shocks can make immediate price adjustment more costly for the individual firm if other firms have not already adjusted their prices, which can slow price adjustment in response to demand shocks (Yeager 1997). On the other hand, if firms set prices by marking up over costs, then their response to supply shocks can be prompt. Thus it is plausible that firms react faster to supply shocks than demand shocks.\footnote{See Okun 1981, pp. 148–154.} Further still, firms may see demand shocks as transient compared to supply shocks, and may therefore wait longer to adjust to demand shocks in case conditions revert.
The goal of this paper is to test this proposition using a simple aggregate demand and supply model using the Calvo parameter to model price-stickiness. The procedure is as follows: first, theoretical impulse response functions are derived from the model. Next, the empirical impulse response functions are estimated from the data, using identification schemes from Blanchard and Quah (1989), and from Uhlig (2005). Then the Calvo parameter is estimated separately for supply and demand shocks, along with the other parameters. Finally, the residuals from the vector autoregression are resampled to create a large number of synthetic empirical response functions, which are then used to approximate the distribution of the estimated values for the Calvo parameter, both for all shocks and separately for supply and demand shocks. This approximate distribution is then used to characterize the uncertainty regarding the point estimate for the value of the parameter that would best fit the empirical impulse response functions if they were known exactly.

Based on the point estimate from the Blanchard-Quah identification, and based on the bootstrapped distribution for the Calvo parameter, it is extremely unlikely that the average period of adjustment following supply shocks differs by a quarter or more from the average period of adjustment following demand shocks. The sign restriction identification from Uhlig suggests a slightly larger difference, but the separate estimates are still quite close.
2. Theory

To generate theoretical impulse response functions, I use a simple aggregate demand and supply model consisting of a short-run aggregate demand curve, a short-run aggregate supply curve, and a long-run aggregate supply curve. The model is then solved for a bivariate ARMA(1, ∞) process in output and the price-level. From the solved model, theoretical impulse response functions for supply and demand shocks are derived. The theoretical impulse response functions can then be used to estimate the Calvo parameter separately for supply and demand shocks by varying the parameters to best match the empirical impulse response functions estimated from the data.

2.1 Aggregate Demand

Let $y_t$ and $p_t$ denote the natural log of output and the natural log of the price-level respectively, where the $t$ subscript denotes the time period. The aggregate demand curve is assumed to be linear with slope $-d$. Thus the aggregate demand curve is given as

$$p_t = a_t - dy_t,$$

where $a_t$ is the $p$-intercept. This defines $p_t$ as a function of $y_t$, and so this equation defines the short-run aggregate demand curve. Aggregate demand shocks are defined as horizontal shifts in the aggregate demand curve. Because the slope of the curve is $-d$, this means that the shock can be written as

$$\eta_t = d(a_t - a_{t-1}).$$
Linearity implies that the demand shock in period \( t \), \( \eta_t \), is determined by the points \((y_{t-1}, p_{t-1})\) and \((y_t, p_t)\). Because the short-run aggregate supply curve is linear, there exists a point \((y^*_{t-1}, p^*_{t-1})\) on the short-run aggregate demand curve for period \( t - 1 \) such that \( p^*_{t-1} = p_t \), and because the slope of the curve is \(-d\), there exists some real number \( r \) such that the following vector equations hold:

\[
\begin{bmatrix}
y_{t-1} \\
p_{t-1}
\end{bmatrix} + r \begin{bmatrix}
-1 \\
d
\end{bmatrix} = \begin{bmatrix}
y^*_{t-1} \\
p^*_{t-1}
\end{bmatrix} = \begin{bmatrix}
y_t \\
p_t
\end{bmatrix} + \begin{bmatrix}
\eta_t \\
0
\end{bmatrix}
\]

This yields the following equation for the dynamics of the short-run aggregate demand curve:

\[
p_t - p_{t-1} = -d(y_t - y_{t-1}) + d\eta_t \quad (2.1)
\]

### 2.2 Long-Run Aggregate Supply

Next, we can define the long-run aggregate supply curve to be a vertical line defined by \( y^f_t \), where \( y^f_t \) denotes the level of output under flexible prices in period \( t \). We define supply shocks as

\[
\epsilon_t = y^f_t - y^f_{t-1}. \quad (2.2)
\]

It is clear that the supply shock is equal to the horizontal shift in the long-run aggregate supply curve between periods.

The flexible price-level \( p^f_t \) is in turn determined by the intersection of the long-run aggregate supply curve and short-run aggregate demand curve, and because the slope of the short-run aggregate demand curve is \(-d\), this yields

\[
p_t - p^f_t = -d(y_t - y^f_t) \quad (2.3)
\]
2.3 Staggered Pricing and Short-Run Aggregate Supply

In this model, price-stickiness is modeled using a Calvo parameter. In the Calvo model, it is assumed for simplicity that there are an infinite number of identical firms. In each period, a constant portion of firms are permitted to adjust their price in period \(t\), and all other firms must keep the same price as in period \(t-1\). The portion of firms prevented from changing their price in each period is \(\omega\), which is the Calvo price-stickiness parameter or simply the Calvo parameter. When firms are permitted to adjust their price, they set prices to the flexible price-level \(p_f^t\).

The Calvo model for price-stickiness implies that the price-level in period \(t\) is a weighted average of the price that firms that are allowed to change their price set, denoted \(p_f^t\) for the flexible price-level, and of the price-level in the previous period, \(t-1\). Since the portion of all firms that are allowed to change their price is \(1 - \omega\) where these firms set their prices collectively to the flexible price-level \(p_f^t\), and since the proportion of firms that are not allowed to change their price is \(\omega\) where these firms are stuck with their prices at \(p_{t-1}\), the the weights on \(p_f^t\) and \(p_{t-1}\) are \(1 - \omega\) and \(\omega\) respectively, which yields

\[
p_t = \omega p_{t-1} + (1 - \omega)p_f^t
\]  

(2.4)

Compare this equation with equation (12) in Kiley (2002).
2.4 The Solved Model

We collect equations (2.1), (2.2), (2.3), and (2.4) from above and solve for \( y_t \) and \( p_t \) in terms of \( y_{t-1}, p_{t-1}, y_0^f, \eta_t, \) and \( \epsilon_j \) for \( j = 1, 2, \ldots, t \) to get the following system of equations:

\[
\begin{bmatrix}
y_t \\
p_t
\end{bmatrix} = \begin{bmatrix}
\omega & 0 \\
1 - \omega & 1
\end{bmatrix} \begin{bmatrix}
y_{t-1} \\
p_{t-1}
\end{bmatrix} + \left( y_0^f + \sum_{j=1}^{t-1} \epsilon_j \right) \begin{bmatrix}
1 - \omega \\
-(1 - \omega)
\end{bmatrix} \begin{bmatrix}
1 - \omega & \omega \\
-d(1 - \omega) & d(1 - \omega)
\end{bmatrix} \begin{bmatrix}
\epsilon_t \\
\eta_t
\end{bmatrix}
\]

Note that this is a bivariate ARMA\((1, \infty)\) process.

2.5 Theoretical Impulse Response Functions

Now that the theoretical model is solved for in the variables \( y_t \) and \( p_t \), the next step is to derive the theoretical impulse response functions. The theoretical impulse response functions are as follows: the response of \( y_t \) to a unit supply shock, the response of \( y_t \) to a unit demand shock, the response of \( p_t \) to a unit supply shock, and the response of \( p_t \) to a unit demand shock, which are denoted as \( f_{y,\epsilon}(t) \), \( f_{y,\eta}(t) \), \( f_{p,\epsilon}(t) \), and \( f_{p,\eta}(t) \) respectively.

Each of the impulse response functions, \( f_{x,\xi} \), is defined by the change in \( x_t \) due to a one unit increase in \( \xi_1 \), where \( x_t = y_t, p_t \) and \( \xi_1 = \epsilon_1, \eta_1 \).

Solving first for the response of output to a unit supply shock, the expression is

\[
f_{y,\epsilon}(t, \omega) = 1 - \omega^t
\]

(2.5)

The response of output to a unit demand shock is given by

\[
f_{y,\eta}(t, \omega) = \begin{cases} 
0, & t = 0 \\
\omega^t, & t \geq 1 
\end{cases}
\]

(2.6)
Next, the response of the price-level to a unit supply shock is given by

\[ f_{p,\epsilon}(t, \omega, d) = d(\omega^t - 1) \] (2.7)

Finally, the response of the price-level to a unit demand shock is given by

\[ f_{p,\eta}(t, \omega, d) = d(1 - \omega^t) \] (2.8)

The four equations (2.5), (2.6), (2.7), and (2.8) give us the theoretical impulse responses for both output and the price-level with respect to both supply shocks and demand shocks in terms of the Calvo parameter, \( \omega \), which can be used to fit the theoretical impulse response functions to the empirical impulse response functions which will be estimated in the next section. The four theoretical impulse response functions are graphed in Figure 2.1.

Figure 2.1: Theoretical Impulse Response Functions for \( \omega = 0.8 \) and \( d = 2 \)
3. Empirics

To estimate empirical impulse response functions for output and the price-level for supply and demand shocks, it is first necessary to identify these shocks using the data. This is done two different ways: first by using the Blanchard-Quah (1989) identifying restrictions, in which demand shocks are identified by requiring that the long-run effect of demand shocks on output be zero, and second by using Uhlig’s (2005) sign restriction identifying restrictions, in which demand shocks are identified by requiring them to have a positive effect on output and the price level. Once the supply and demand shocks are identified, empirical impulse response functions can be estimated from the data, to which the theoretical impulse response functions can be fit.

3.1 Data

Monthly data for the Industrial Production Index (INDPRO) and the Consumer Price Index for Urban Consumers: All Items (CPIAUCSL) for January 1975 to January 2000 were obtained from the Federal Reserve Economic Database (FRED). The data range was selected to begin after the end of the 1973 oil crisis, as using data from January 1950 to January 2000 resulted in a positive response in the price-level to supply shocks and a negative response in the price-level to demand shocks. Since this is inconsistent with the structural interpretation I want to give to the two shocks identified by Blanchard and Quah’s restrictions, I omitted data before 1975. This is similar to the findings of Keating and Nye (1998 and 1999) for several other data sets, and suggests that in the data there are at least two different kinds of supply shocks that significantly affect output and the price-level. This invalidates the
structural interpretation usually given to the shocks identified with Blanchard and Quah’s restrictions. Nevertheless, using the later data set does not result in these problems.

Following the procedure used in Cover, Enders, and Hueng (2006), augmented Dickey-Fuller tests of the natural logs of Industrial Production Index and the CPI were run to test for stationarity. At the 95% confidence level, the augmented Dickey-Fuller tests rejected the null hypothesis of stationarity for both the natural log of Industrial Production Index and the natural log of the CPI. Both time series were differenced once and the test was run again. The test indicated that both the first difference of the natural log of Industrial Production Index and of CPI were stationary. Hence, the data used in the vector autoregression to identify the supply and demand shocks are the first difference of the natural log of Industrial Production Index and the first difference of the natural log of the CPI.

Two selection criteria are used to determine the optimal lag length for the vector autoregression. These are the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC). The criteria indicated optimal lag lengths of nine and two months, respectively. Of these two criteria, the AIC was used as the criterion for the VAR. Hence the lag length is set to nine months.

3.2 Blanchard-Quah Identification

Under the Blanchard-Quah Identifying restrictions, it is assumed that there are two types of shocks determining output and the price-level. One of these shocks is assumed to have no long-run effect on output, and it is this shock that is labeled the “demand shock.” The other shock is then labeled the “supply shock.” These shocks are assumed to be uncorrelated. It is assumed that the shocks to the bivariate Wold decomposition of $y_t$ and $p_t$ are linear combinations of the underlying supply and demand shocks.
These assumptions imply that $x_t = (\Delta y_t, \Delta p_t)$ follows a stationary process

$$x_t = \sum_{j=0}^{\infty} A_j e_{t+j}, \quad \Var(e) = I$$

where the $A_j$ are $2 \times 2$ matrices whose upper left-hand entries sum to zero, and where the $e_{t+j}$ are the shocks to the bivariate Wold decomposition of $x_t$. Since the shocks are uncorrelated, we can normalize the process such that the covariance matrix of the shocks is the identity matrix, $I$.

This representation of the data generating process can be recovered from the data by first estimating and then inverting a vector autoregression of the data to obtain a moving average representation

$$x_t = \sum_{j=0}^{\infty} C_j v_{t+j}, \quad \Var(v) = \Omega$$

where $C_0 = I$. From this, it is clear that the underlying shocks are related to the errors in the estimated process by

$$v_t = A_0 e_t$$

thus

$$A_j = C_j A_0$$

for all periods $j$. The matrix $A_0$ is obtained by using the restrictions that $\sum_{j=0}^{\infty} a_{11,j} = [(\sum_{j=0}^{\infty} C_j) A_0]_{11} = 0$, $A_0 A_0^T = \Omega$.

### 3.3 Sign Restriction Identification

To use sign restrictions to identify supply and demand shocks, the matrix $A_0$ is instead identified by requiring that the implied empirical impulse response functions satisfy the restriction that the effects on output and the price-level of a demand shock be positive.
This is done by following the procedure outlined in Uhlig (2005). First, a vector \( \tilde{a} \in \mathbb{R}^2 \) is drawn from a standard normal distribution. Then \( \tilde{a} \) is left-multiplied by \( C \), where \( C \) is the inverse of the Cholesky factor of \( \Omega \). The result is normalized, and labeled \( a \). The matrix \( A_0 \) is constructed by making the vector \( a \) one of its columns, and then by solving for the other column using the fact that \( \Omega = A_0 A_0^T \). Finally, the impulse response functions are calculated as above, and are checked against the sign restrictions. This procedure is repeated 10,000 times and all of the impulse response functions that satisfy the sign restrictions are kept.

### 3.4 Empirical Impulse Response Functions

Using a lag length of nine months as indicated by the above tests, a vector autoregression is estimated for the first difference of the Industrial Production Index and the first difference of the natural log of the CPI. The Blanchard-Quah restriction requires that the long-run response of output to demand shocks be zero.

The empirical impulse response functions for both output and the price-level with respect to both supply shocks and demand shocks were estimated and are plotted below for 150 periods, enough time for the responses to converge to their long-run levels.

The justification for this restriction is the hypothesized long-run neutrality of money. Because the model is structured so that demand shocks are identical to monetary shocks, the long-run effect of a demand shock on output should be zero. Note that this is true of the theoretical model, as can be seen in the theoretical impulse response function of output with respect to a demand shock:

\[
\lim_{j \to \infty} f_{y,\eta}(j) = \lim_{j \to \infty} \omega_j = 0
\]

Hence the shock identified by the Blanchard-Quah restrictions as the one that has a zero
long-run effect on output can be identified with the monetary or demand shock described in the theoretical model. And, therefore, we can identify the theoretical impulse response functions with the estimated empirical impulse response functions. The error bands for this estimation are calculated by bootstrapping using the residuals from the vector autoregression. The empirical impulse response functions and the corresponding 95% error bands are given in Figure 3.1, with the error bands in gray. The median, 5%, and 95% quantiles for the sign restriction identified empirical impulse response functions are given in Figure 3.2.

Figure 3.1: Empirical Impulse Response Functions from the Blanchard-Quah Identification
Figure 3.2: Empirical Impulse Response Functions from the Sign Restriction Identification
4. Estimation

There are four parameters to estimate in order to match the theoretical impulse response functions to the empirical impulse response functions: the Calvo price-stickiness parameter, $\omega$; the slope of the aggregate demand curve, $d$; the standard deviation of the supply shock, $\sigma_\epsilon$; and the standard deviation of the demand shock, $\sigma_\eta$. Recall that theoretical impulse response functions are denoted by $f_{y,\epsilon}, f_{y,\eta}, f_{p,\epsilon},$ and $f_{p,\eta}$ where the first subscript denotes the variable subject to the shock and the second subscript denotes what type of shock the variable has been subjected to. The empirical impulse response functions are denoted by

$$\frac{\partial y_{t+j}}{\partial \epsilon_t}(j), \frac{\partial y_{t+j}}{\partial \eta_t}(j), \frac{\partial p_{t+j}}{\partial \epsilon_t}(j), \text{ and } \frac{\partial p_{t+j}}{\partial \eta_t}(j).$$

4.1 The Calvo Parameter

The theoretical impulse response functions are fit to the empirical impulse response functions by minimizing the sum of the squared errors, i.e. the $\ell^2$ distance, between them. This is defined as

$$\text{SSE}_{\text{all}}(\omega, d, \sigma_\epsilon, \sigma_\eta) = \sum_{j=0}^{n} \left( (\sigma_\epsilon f_{y,\epsilon} - \frac{\partial y_{t+j}}{\partial \epsilon_t})^2 + (\sigma_\epsilon f_{p,\epsilon} - \frac{\partial p_{t+j}}{\partial \epsilon_t})^2 + (\sigma_\eta f_{y,\eta} - \frac{\partial y_{t+j}}{\partial \eta_t})^2 + (\sigma_\eta f_{p,\eta} - \frac{\partial p_{t+j}}{\partial \eta_t})^2 \right)$$

where $n$ is the length of the generated empirical impulse response functions. I chose $n$ to be 150 for both the Blanchard-Quah identified empirical impulse response functions and the sign-restriction identified empirical impulse response functions, as this gives the empirical impulse response functions long enough to converge to their long-run values. The estimated
<table>
<thead>
<tr>
<th>Variable/Parameter</th>
<th>Values for Blanchard-Quah</th>
<th>Values for Sign-Restriction</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\omega^*$</td>
<td>0.950</td>
<td>0.991</td>
</tr>
<tr>
<td>$d^*$</td>
<td>0.906</td>
<td>1.622</td>
</tr>
<tr>
<td>$\sigma^*_\epsilon$</td>
<td>1.005</td>
<td>0.052</td>
</tr>
<tr>
<td>$\sigma^*_\eta$</td>
<td>0.708</td>
<td>0.470</td>
</tr>
<tr>
<td>$\text{SSE}_{\text{total}}$</td>
<td>1.318</td>
<td>2.003</td>
</tr>
</tbody>
</table>

Table 4.1: Minimizing Values for $\text{SSE}_{\text{total}}$ Using Blanchard-Quah Identification

values and the values of the sum of the squared errors are reported in Table 4.1.

The Calvo parameter $\omega$ is now estimated separately for the supply shocks and the demand shocks. To do this, two new functions are defined, $\text{SSE}_{\text{supply}}$ and $\text{SSE}_{\text{demand}}$, as follows:

$$\text{SSE}_{\text{supply}}(\omega, d, \sigma_\epsilon) = \sum_{j=0}^{n} \left( (\sigma_\epsilon f_{y,\epsilon} - \frac{\partial y_{t+j}}{\partial \epsilon_t})^2 + (\sigma_\epsilon f_{p,\epsilon} - \frac{\partial p_{t+j}}{\partial \epsilon_t})^2 \right)$$

$$\text{SSE}_{\text{demand}}(\omega, d, \sigma_\eta) = \sum_{j=0}^{n} \left( (\sigma_\eta f_{y,\eta} - \frac{\partial y_{t+j}}{\partial \eta_t})^2 + (\sigma_\eta f_{p,\eta} - \frac{\partial p_{t+j}}{\partial \eta_t})^2 \right)$$

The minimizing values for these are reported in Table 4.2.

The average period of price adjustment corresponding to $\omega^*$ is given by $1/(1 - \omega^*) = 20$. Note that the value of $\omega^*$ suggests a much longer average period of price adjustment than six months, which is the length suggested by other research on the frequency of price adjustment in Calvo-style models (Eichenbaum and Fisher 2007).

4.2 Characterizing Uncertainty

Using the residuals from the vector autoregression from before, synthetic time series of output and inflation can be constructed which give some idea of the uncertainty placed on the estimate from the Blanchard-Quah identification. The technique used to construct a
distribution of possible values for \( \omega \) is to apply the calibration technique used above to 3,000 synthetic time series. The resulting probability distribution for \( \omega \) is given in Figure 4.5 below.

Similarly, the uncertainty around the difference between the separately calibrated values can be characterized by applying the separate calibration procedures above to the same 3,000 synthetic time series. The distribution of \( \omega_{\text{supply}} - \omega_{\text{demand}} \) is given in Figure 4.5 below.

Both of these distributions can be transformed to give distributions of the average period of adjustment over all firms using the function \( f(\omega) = \frac{1}{1 - \omega} \). The transformed distributions are also given in Figure 4.5.

Similar distributions are also calculated for all of the empirical impulse response functions...
Figure 4.2: Calibrated Theoretical Impulse Response Functions and Empirical Impulse Response Functions for Sign Restriction Identification

generated by the sign restriction identifications. These are given in Figure 4.6. Note that the transformed distribution appears to give significant differences in the average period of adjustment between supply and demand shocks. However, this is because $f(\omega)$ has a singularity at $\omega = 1$. Looking at the distribution of the parameter shows that the difference is insignificant.
Figure 4.3: Separately Calibrated Calvo Parameter Theoretical Impulse Response Functions and Empirical Impulse Response Functions for Blanchard-Quah Identification

<table>
<thead>
<tr>
<th>Parameter/Variable</th>
<th>Values for Blanchard-Quah</th>
<th>Values for Sign-Restriction</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\omega^*_{\text{supply}}$</td>
<td>0.952</td>
<td>0.951</td>
</tr>
<tr>
<td>$\omega^*_{\text{demand}}$</td>
<td>0.953</td>
<td>0.991</td>
</tr>
<tr>
<td>$\sigma^*_{\epsilon,\text{supply}}$</td>
<td>1.012</td>
<td>0.030</td>
</tr>
<tr>
<td>$\sigma^*_{\eta,\text{demand}}$</td>
<td>0.586</td>
<td>0.457</td>
</tr>
<tr>
<td>$d^*_{\text{supply}}$</td>
<td>0.900</td>
<td>1.619</td>
</tr>
<tr>
<td>$d^*_{\text{demand}}$</td>
<td>1.105</td>
<td>1.741</td>
</tr>
<tr>
<td>SSE$_{\text{supply}}$</td>
<td>0.549</td>
<td>0.075</td>
</tr>
<tr>
<td>SSE$_{\text{demand}}$</td>
<td>0.635</td>
<td>1.793</td>
</tr>
</tbody>
</table>

Table 4.2: Minimizing Values for Separate Calibrations
Figure 4.4: Separately Calibrated Calvo Parameter Theoretical Impulse Response Functions and Empirical Impulse Response Functions for Sign Restriction Identification
Figure 4.5: Distributions for Blanchard Quah Identification
Figure 4.6: Distributions for Sign Restriction Identification
5. Conclusion

While the difference in the separately estimated values of $\omega$ for supply and demand shocks for the Blanchard-Quah identified empirical impulse response functions does not provide any evidence that there is a difference in the speed of price adjustment following supply and demand shocks, the statistical test provided by the synthetic time series does suggest there is some economically significant difference in how “sticky” prices are in response to supply shocks versus demand shocks. The median difference in the average period of adjustment is over four months. This finding is, however, contingent on both the simple aggregate supply and aggregate demand model and Blanchard and Quah’s identification. As noted before, Blanchard and Quah’s identification scheme does not always easily lend itself to the preferred structural identification, where the shock that has no long-run effect on output is identified as a demand shock and the other shock as a supply shock. As such, this result cannot be considered conclusive, and more work is needed to address this potential problem. This is especially true because, according to Okun, “There is overwhelming evidence that firms in most industries adjust prices more promptly and reliably to changes in cost than in responses to changes in demand.”

The sign restriction identification does not fit the model well enough to provide very meaningful results, but even so, the difference in the estimated values of the Calvo parameter are very small.

If another, more reliable method of identifying supply and demand shocks from macroeconomic data could show a larger difference in the fit of a theoretical model to macroeconomic

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data when separate measures are allowed for price stickiness in response to supply shocks versus price stickiness in response to demand shocks, then it would be plausible that theoretical models featuring different parameters for price stickiness for the two shocks would better fit the data. The use of another model, such as a New Keynesian model, could also give different results, such as in Dupor, Han, and Tsai (2009), who find a difference using a related procedure.
6. References


