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Choice of Aggregate Demand Proxy and its Affect on Phillips Curve Nonlinearity: U.S. Evidence

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Abstract

Using nonlinearity testing and modeling associated with the smooth transition regression model we examine how the choice of aggregate demand proxy affects, if at all, the nonlinearity of the Phillips curve. The three proxies we examine are the unemployment rate, output gap, and real unit labor costs. Our data is monthly from 1983-2008 for the U.S. We find that regardless of aggregate demand proxy examined, tests indicate a nonlinear Phillips curve. However, the dynamics of the nonlinear models vary substantially.

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1. Introduction

Two primary issues related to the Phillips curve, the relationship between inflation and a proxy for aggregate demand are the shape of the curve and the choice of proxy. Is the Phillips curve linear or nonlinear, and if nonlinear, of what form? Three common choices for aggregate demand proxy are a measure of output (such as the output gap), the unemployment rate, or real unit labor costs. We explore how the choice of proxy affects, if at all, the conclusion about shape. To do this, we employ the nonlinear testing and modeling strategy of the smooth transition regression (STR) framework using monthly data (1983 to 2008) for the U.S. Our analysis will be of interest to practitioners, especially those interested in nonlinear modeling. In particular for practitioners that use a Phillips curve to forecast inflation or those that use a Phillips curve for evaluation of policy or calibration of theoretical models.

We follow the STR testing strategy described in Escribano and Jorda (1998) and followed in Stimel (2009), first specifying a linear Phillips curve and testing against a nonlinear alternative. If linearity is rejected we model the nonlinearity with the STR model as in Luukkonen, Saikkonen, and Terasvirta (1988), Terasvirta (1994), and Escribano and Jorda (1998). We use this model because it may better capture microfoundational forces. If the underlying Phillips curve nonlinearity in individual labor or goods markets is discrete or of various forms, once aggregated, it is more likely to be smoothed (Stimel, 2009). Two previous studies of the U.S. Phillips curve use this framework with contradictory results. Eliasson (2001) presents evidence against nonlinearity using post-1982 monthly data while Stimel (2009) finds evidence in favor of it with post-WWII quarterly data. One possible explanation for the difference is temporal aggregation similar to the findings of Paya and Peel (2006) in an investigation of nonlinearity in purchasing power parity.

We find evidence to reject linearity in the U.S. Phillips curve regardless of aggregate demand proxy chosen. However, in specifying, estimating, and analyzing the nonlinear STR models, we find the dynamics of the economy vary depending on the aggregate demand proxy. In particular we find that with real unit labor costs, the differences between regimes with regard to Phillips curve slope are relatively small and may not be of much practical importance. For the unemployment rate model, we find the regimes are closely related to the business cycle. For the output gap model, there are noticeable differences between regimes, but no obvious tie to the business cycle.

2. Literature Review

Many theoretical investigations focus on the implications of nonlinearity of the Phillips curve for policy purposes. Examples include Clark, Laxton, and Rose (1996), Dolado, Maria-Dolores, and Naveria (2005), and Akerlof and Yellen (2006). In an empirical study, Kim, Osborn, and Sensier (2007) find evidence that with a nonlinear Phillips curve (inflation and output gap) a monetary policy rule is nonlinear pre-1979 but only weakly so post-1979.

An issue in empirical studies is the choice of proxy for aggregate demand. The unemployment rate has historically been used based on the examination of wages and unemployment in the original work of Phillips (1958). When Samuelson and Solow (1960) reformatted the relationship as an inverse relation between inflation and unemployment in order to close the Keynesian macro model, it seems to have cemented the role of the unemployment rate. For example, modern examinations such as Gordon (1998), Staiger, Stock, and Watson (2001), or Cogley and Sargent (2001) also use the unemployment rate. The use of an output measure, typically some form of output gap, is common in the New Keynesian Phillips curve literature. The New Keynesian Phillips curve is a forward-looking Phillips curve, where inflation depends on expected inflation and current real marginal cost. It is commonly derived with microfoundations based on Calvo (1983). Due to inadequacies in the theory matching certain characteristics in the data, particularly inflation persistence, various hybrid versions that include a backward-looking component (lagged inflation as an explanatory variable) abound. These include Fuhrer and Moore (1995) and Christiano, Eichenbaum, and Evans (2005) among others. One of the more recent debates has been that instead of the output gap, using real unit labor cost or labor's share of income as the aggregate demand proxy (Gali and Gertler, 1999 and Sbordone, 2002). Finally, a very detailed survey of these recent Phillips curve debates is in Rudd and Whelan (2005).

3. Linear Phillips Curve

One way to specify a standard expectations-augmented Phillips curve is that deviations of inflation from expected inflation (π - π^e) are a function of a proxy for aggregate demand (X), supply shocks (Z) and an error term (ε). Recognizing the possibility of dynamics in the economy, we add lagged terms for each explanatory variable including the dependent variable. The reduced-form specification is illustrated in equation (1).

$$\left(\pi-\pi^{e}\right)_{t}=\alpha+\beta_{\pi}(L)\left(\pi-\pi^{e}\right)_{t-1}+\beta_{X}(L)X_{t-1}+\beta_{Z}(L)Z_{t-1}+\varepsilon_{t} \qquad (1)$$

In equation (1), the parameters to be estimated are the intercept, α, slope coefficients, $\beta_\pi(L)$, $\beta_X(L)$, and $\beta_Z(L)$, and the error term, ε. This curve only contains backward-looking terms. This is consistent with Nason and Smith (2008) who find little support for forward-looking terms in the New Keynesian Phillips curve.

Appendix A describes the data and sources. For the supply shock, we use the growth rate of food and energy prices. Following Gordon (1998) the variable is defined as having zero mean over the sample. This imposes that the nonaccelerating inflation rate of unemployment (*NAIRU*) or equivalent for alternate aggregate demand proxies are unaffected by the supply shock. *NAIRU* is the rate of unemployment rate that is consistent with $\pi = \pi^e$. By definition, $NAIRU=\frac{-\alpha}{\beta_{X}(L)}$, and with zero mean, Z does not affect the intercept, α. The proxies of aggregate demand (X) we use are the output gap (OG), real unit labor cost gap (ULC), and the unemployment rate (UR). For the real unit labor cost gap and output gap, the gap is the percentage deviations from trend estimated with the Hodrick-Prescott filter.

Table 1 shows the results of augmented Dickey-Fuller tests where the null hypothesis is that the series contains a unit root. We include a constant and a trend in the test and allow for up to twelve lags. The lag length is selected using the Akaike Information Criterion (AIC). Based on the unit root tests, we reject the presence of a unit root in each series over the sample at a 5% test size.

The common sample is 1978-2008 and the data is monthly. However, we chose to start the sample at 1983 for two reasons. First, we are concerned about the unusual period of 1979-1982, known as the non-borrowed reserves targeting era. This era is commonly recognized in the monetary literature as a policy regime shift. Since a discussion of the Phillips curve is hard to disentangle from a discussion of monetary policy, we chose to remove this possible structural break from our sample. Second, there is macroeconomics research on the "Great Moderation", the observed reduction of volatility in many macroeconomic time series in the 1980s onward relative to the earlier era (see McConnell and Perez-Quiros, 2000). This would also constitute a possible structural break.

Table 2 shows the estimates of equation (1) using ordinary least squares (OLS) with Newey-West corrected standard errors (based on serial correlation tests) for each aggregate demand proxy. We again use AIC to select the lag length for the explanatory variables in each regression, allowing a maximum of twelve lags. Results using AIC suggest 11 lags of each variable, regardless of the choice of X.

One interesting result from *Table 2* is the estimated coefficient sum for the lagged dependent variable (π - π^e). As discussed in Rudd and Whelan (2005), the hypothesis, H_0: $\beta_\pi(L) = 1$ versus H_A: $\beta_\pi(L) < 1$ is a traditional test of the natural rate hypothesis of Friedman (1968) and Phelps (1968). Failure to reject the null is an indication that the natural rate hypothesis is true, namely that there is no long-run tradeoff between inflation and aggregate demand. Rejection of the null indicates there is a long-run tradeoff. Cogley and Sargent (2001) express concern that due to improved monetary policy there may be erroneous empirical findings that do not support the natural rate hypothesis. Their fears seem true in two of the three cases here. It is only when the unemployment rate (*UR*) is used that the test fails to reject the null.

Another interesting result from *Table 2* is that the sign on the supply shock terms, regardless of the proxy used is not the sign we would expect. We would expect a rise in food and energy prices to push inflation higher rather than push it slightly lower as we find here. One possible explanation is that we are capturing an effect of monetary policy. A forward-looking monetary authority that observes food and energy prices rising will begin to tighten policy in order to hold down inflation expectations and ultimately inflation (the so-called nominal anchor). Thus we might see a negative association of inflation and food and energy prices, as they are both affected by the response of monetary policy.

Finally, it is interesting to note the small coefficient sums for each $\beta_X(L)$ in *Table 2*. These indicate a relatively flat Phillips curve, a small magnitude slope. This implies, even in the short run, a relative small inflation and aggregate demand tradeoff over this period. For example, based on the result, a 1% rise in output above trend generates only a 0.05 percentage point increase in inflation above expected inflation. This result is the "disappearance of the Phillips curve" discussed in Gordon (1998), Brayton, Roberts, and Williams (1999), and Staiger, Stock, and Watson (2001).

4. Nonlinear Model and Testing Strategy

The alternative model is the smooth transition regression (STR) model, shown in equation (2).

$$\begin{aligned}(\pi-\pi^e)_t = {} & \delta + \lambda_\pi(L)(\pi-\pi^e)_{t-1} + \lambda_X(L)X_{t-1} + \lambda_Z(L)Z_{t-1} + \\ & \{\mu + \theta_\pi(L)(\pi-\pi^e)_{t-1} + \theta_X(L)X_{t-1} + \theta_Z(L)Z_{t-1}\}F(S_{t-d},\gamma,c) + \nu_t\end{aligned} \qquad (2)$$

The nonlinearity stems from the function $F(S_{t-d}, \gamma, c)$ called the transition function, which typically is the logistic (LSTR) or exponential (ESTR) function (Anderson and Terasvirta, 1992 and Escribano and Jorda, 1998). The variable, S_{t-d}, is one of the lagged explanatory variables (d is the lag length) and is determined in conjunction with the nonlinearity tests. To be estimated is γ, the slope or speed of the transition between regimes (i.e., it determines whether the regime switch occurs quickly between two months, slowly over a year, etc.). Also to be estimated, c, defines the position of the transition. To aid in interpretation, define the "low" regime to be when $F(S_{t-d}, \gamma, c) = 0$ and the "high" regime to be when $F(S_{t-d}, \gamma, c) = 1$. Notice that equation (2) is linear in the two regimes. At any point in time, the dynamics of the economy then are defined as a weighted average of these two linear regimes, where $F(S_{t-d}, \gamma, c)$ determines the weights. This give the model its smooth changes between regimes.

If instead of the logistic or exponential function $F(S_{t-d}, \gamma, c)$ were a simple indicator function of 0 or 1, this model would collapse to a simple regime-switching model similar to Hamilton (1989). Or, if $F(S_{t-d}, \gamma, c)$ is the logistic function, and $\gamma \rightarrow \infty$, equation (2) becomes a standard Threshold Autoregressive (TAR) model (Escribano and Jorda, 1998). Thus one attractive feature of the STR model is that it can be viewed as encompassing other threshold or regime-switching models.

In equation (2), δ, $\lambda_\pi(L)$, $\lambda_X(L)$, and $\lambda_Z(L)$, are the intercept and slope coefficients for the "low" regime. For the "high" regime, $(\delta + \mu)$ is the intercept, $[\lambda_\pi(L) + \theta_\pi(L)]$, $[\lambda_X(L) + \theta_X(L)]$, and $[\lambda_Z(L) + \theta_Z(L)]$ are the slope coefficients. The error term is υ. Notice that the model slightly more than doubles the number of coefficients to be estimated. This can be a drawback if there is a lack of degrees of freedom. However, here we do not have that problem. We have 312 observations and 70 parameters to estimate in equation (2).

For the nonlinear testing and selection of the appropriate model, we follow Escribano and Jorda (1998) and we refer interested readers there for more detail and derivations. In brief, the function $F(S_{t-d}, \gamma, c)$ is replaced with its Taylor series approximation (around $\gamma = 0$), equation (2) estimated, and the coefficients that interact with the approximation are jointly tested for significance. In effect, the null of linearity is tested against the alternative of nonlinearity with a Lagrange Multiplier test. The test statistic is distributed Chi-square but the F-distribution is commonly used due to its small sample properties (Escribano and Jorda, 1998).

Recall that S_{t-d} will be one of the lagged explanatory variables, but we don't know which one. The empirical solution is to try every lagged explanatory variable as a possible S_{t-d} and select the S_{t-d} that corresponds to the smallest p-value or equivalently, largest Lagrange Multiplier test statistic from the nonlinearity test (Luukkonen, Saikkonen, and Terasvirta, 1988, Terasvirta, 1994, and Escribano and Jorda, 1998). Thus we simultaneously test the null of linearity as well as select S_{t-d}. This could be viewed as data mining as we are searching the data trying every possible candidate for S_{t-d} and then choosing the one that provides the best test result. However, the use of this type of strategy is similar to a sup *LM* test and not uncommon in empirical work. For example, in the structural break testing methodology of Bai and Perron (1998), they use an analogous test to aid in the selection of unknown break dates.

Finally, assuming linearity is rejected and S_{t-d} is chosen with the above methodology, the choice of functional form remains. The literature defines two F-tests designed to exploit the fact for the Taylor series approximation of the logistic function, the even powers will be 0 and for the exponential function, the odd powers will be 0 (see Escribano and Jorda, 1998; 2001). Thus we test the joint significance of the coefficients associated with the even powers versus the odd powers. If the "even" test has a smaller p-value (larger test statistic) then the exponential function is the appropriate choice. If it is the "odd" test has a smaller p-value, then the choice is the logistic function. Some monte carlo evidence of the efficacy of the method is presented in Escribano and Jorda (2001).

5. Nonlinear Test Results

With 3 different aggregate demand proxies and 33 lagged variables (3 explanatory variables, each with 11 lags as candidates for S_{t-d}), we conduct 99 different nonlinear tests in total. We evaluated the Lagrange Multiplier tests with both the F-distribution version and the Chi-square distribution version. The overall results were similar and the ultimate conclusion about the transition variable (S_{t-d}) was the same. Regardless of which distribution is used there is a support for rejecting the null of linearity. Using a 10% test size, roughly 80% of the tests reject the null of linearity using the F-distribution version and 90% with the Chi-square distribution version.

Rather than present each of the 99 nonlinearity tests, *Table 3* only shows the best candidate for S_{t-d} per explanatory variable for each aggregate demand proxy specification. From *Table 3* we see that for each aggregate demand proxy, one of the lagged dependent variables is the best candidate for the transition variable. For the output gap, it's the first lag, for the real unit labor cost gap, it's the third lag, and for the unemployment rate it's the fifth lag. It is worth noting that when the real unit labor cost gap is the aggregate demand proxy, the magnitude difference in the Lagrange Multiplier test statistics among the top candidates for the transition variables is small. Also, regardless of the aggregate demand proxy the top candidate for the inflation difference variable is a relatively long lag. Finally, given that in each case the best candidate for transition variable is a lag of the aggregate demand proxy itself, we might expect different dynamics in the estimated nonlinear models. This is because each aggregate demand proxy does not have the exact same dynamic over the business cycle. For example, note that the unemployment rate has the longest lag selected of the three and is itself a lagging business cycle indicator.

Next we conduct the tests to select between the logistic and exponential function following Escribano and Jorda (1998). The results are in *Table 4*. Comparing the tests, for the output gap and the unemployment rate, the exponential function is selected while the logistic function is chosen with the real unit labor cost gap. Given the close magnitude of the result for the unemployment rate specification, robustness of the test result is questionable.

6. Estimation Results and Analysis

We estimate the STR models by nonlinear least squares (NLS). The results are in *Table 5*. To be cautious, the standard errors are Newey-West corrected standard errors. The results presented in *Table 5* are by "high" and "low" regime. Recall that the "high" regime is when the transition function equals one and the "low" regime is when it equals zero. When the output gap or the unemployment rate is the aggregate demand proxy, the

Phillips curve slope switches between regimes. In the case of the output gap, the slope of the Phillips curve is estimated as –0.02 in the "low" regime, but we cannot reject that the coefficients are jointly zero. In the "high" regime, the slope is estimated as 0.09. We have one regime where the slope is positive as expected indicating that increase in aggregate demand increases inflation above expected. In the other regime though, there is either no effect since zero cannot be rejected or possibly a slightly negative effect.

For the unemployment rate, the slope of the Phillips curve is negative as expected in both regimes, but it is more negative (steeper) in the "low" regime. The slope is -0.39 in the "low" regime and –0.09 in the "high" regime as shown in *Table 5*. In contrast to the unemployment rate model and the output gap model, when the real unit labor cost gap is the aggregate demand proxy, the Phillips curve slope difference (0.03 vs. 0.04) is small between regimes. This indicates a more stable relationship and perhaps less added benefit to modeling the nonlinearity in that case. This may also be an added benefit of using real unit labor costs as in the New Keynesian Phillips curve, which assumes linearity in the theoretical model. Finally, from *Table 5*, we see that inflation is highly persistent regardless or aggregate demand proxy and regime. For the food and energy price variable (Z), the sign on the coefficient sums switch depending on the regime.

We graph the transition functions in *Figure 1*. From *Figure 1*, we can clearly see the dynamics of these three models are very different. When real unit labor costs is the aggregate demand proxy, the switches between regimes are frequent and near discrete. Recall that the STR framework can be viewed as encompassing other regime switching models. When real unit labor costs are the aggregate demand proxy, it appears that at a simpler model, a threshold autoregression (TAR) may be more appropriate than the STR model we use. Further, recall from *Table 5* that the differences between regimes are of the least magnitude compared to the other two models with the output gap and unemployment rate. This indicates that an even simpler model, a linear model, may do well enough here even in the presence of nonlinearity.

In contrast, with the unemployment rate model, the transition function fluctuates much less. It is mostly in the "high" regime where the slope of the Phillips curve is relatively flat. Only near recessions does that the model moves toward the low regime and relatively stronger inverse relation between inflation and unemployment. For the output gap, there are lots of fluctuations but no obvious relationship to the business cycle.

7. Conclusions and Questions

A variety of Phillips curve models exist. The choice of aggregate demand proxy is a distinguishing feature. Here in this nonlinear framework, we show that the choice is not trivial. While evidence supports nonlinearity regardless of the aggregate demand proxy used, the nature of that nonlinearity differs substantially between them. This is an important fact for practitioners that rely on a Phillips curve for inflation forecasting or as part of a larger model to analyze business cycles. The dynamics will differ depending on the choice.

Perhaps more troubling for practitioners are the possible stability issues arising from a nonlinear Phillips curve. The frequent regime switches in the output gap model are especially troubling. For example, we are always well aware that macro variables are constructs; they are aggregates from micro level data. There is not a one-to-one mapping from one level to the other. Here we might think of a variety of markets each with its own possibly stable relation between price and market activity. Yet it can very easily be the case that multiple differing outcomes at that level lead to the same relationship at the aggregate level. That suggests a possibility of instability as the underlying individual markets change. This general idea has long been recognized in the Phillips curve literature dating back to Lipsey (1960), but is often ignored and not explicitly addressed. Fok, van Dijk, and Franses (2005) shows a complex relationship between industrial production of different U.S. manufacturing sectors based on business cycle nonlinearity and Hendry (2001) looks at individual markets with a nonlinear framework. Their approaches and our results suggest that looking at the relationship between possible nonlinearities in individual goods and labor markets and how they relate to aggregate business cycle and Phillips curve behavior would be useful.

For theoreticians, the fact that the nonlinearity we find differs by aggregate demand proxy choice raises issues. In the New Keynesian Phillips curve literature, the actual theoretical model derives a linear relationship between real marginal cost and inflation. To get the usual relationship between inflation and the output gap an assumption that output is linearly proportional to real marginal cost is needed (Gali and Gertler, 1999). Given the differences here, that assumption could be questionable. In fact this is what led to the use of real unit labor costs in the New Keynesian Phillips curve literature. It is claimed that real unit labor costs is a better proxy for real marginal costs than the output gap (Gali and Gertler, 1999). Our analysis provides no evidence to answer that question but does show that there is a difference. They have very different dynamics in the data. Given the continued interest in the Phillips curve for macroeconomic analysis and policy such as monetary policy rules, sorting out these issues will continue to be important.

A. Data Sources

Data is monthly and from three online sources: St. Louis Federal Reserve Database (FRED), the University of Michigan's Survey Research Center, and the Conference Board. Growth rates are calculated as year-to-year changes, which removes a little bit of the noise found in monthly data. Trends are calculated using the Hodrick-Prescott (H-P) filter with the standard smoothing parameter setting of 14,400 for monthly data and using the full available sample for the series.

Inflation (π):
The price level is measured using the all-urban consumer price index (*CPI*). The series has the identification CPIAUCSL in FRED and is from 1947:01 to 2008:12. The inflation rate is then calculated as $\pi_t = 100 * \left[\ln(CPIAUCSL)_t - \ln(CPIAUCSL)_{t-12}\right]$.

Expected Inflation (π^e):
Expected inflation is the median expected price change over the next 12 months from a survey of consumers. The series is published by the University of Michigan's Survey Research Center with the series identification MICH and is from 1978:01 to 2008:12.

Supply Shock (Z):
The supply shock is the growth rate of food and energy prices. It is defined as inflation minus core inflation, where core inflation is inflation less food and energy prices. The

core price level is CPILFESL in FRED and is from 1957:01 to 2008:12. Core inflation is calculated in the same manner as the inflation rate. Finally, the supply shock is defined as zero mean by subtracting the mean based on the common sample of 1983:01 to 2008:12 as discussed in the *Section 3*.

Aggregate Demand (*X*): *UR*, *OG*, and *ULC*

Unemployment Rate (*UR*):
The unemployment rate is the civilian rate. The series identification in FRED is UNRATE and is from 1948:01 to 2008:12.

Output Gap (*OG*):
Output is measured as industrial production. The series identification is INDPRO in FRED and is from 1919:01 to 2008:12. The gap is defined as percentage deviations from trend.

Real Unit Labor Cost Gap (*ULC*):
Unit labor costs are labor cost per unit of manufacturing output. The series identification from the Conference Board is A0M062 and is from 1959:01 to 2008:12. The real series is created using CPIAUCSL from FRED as the price level. The gap is the percentage deviations from trend.

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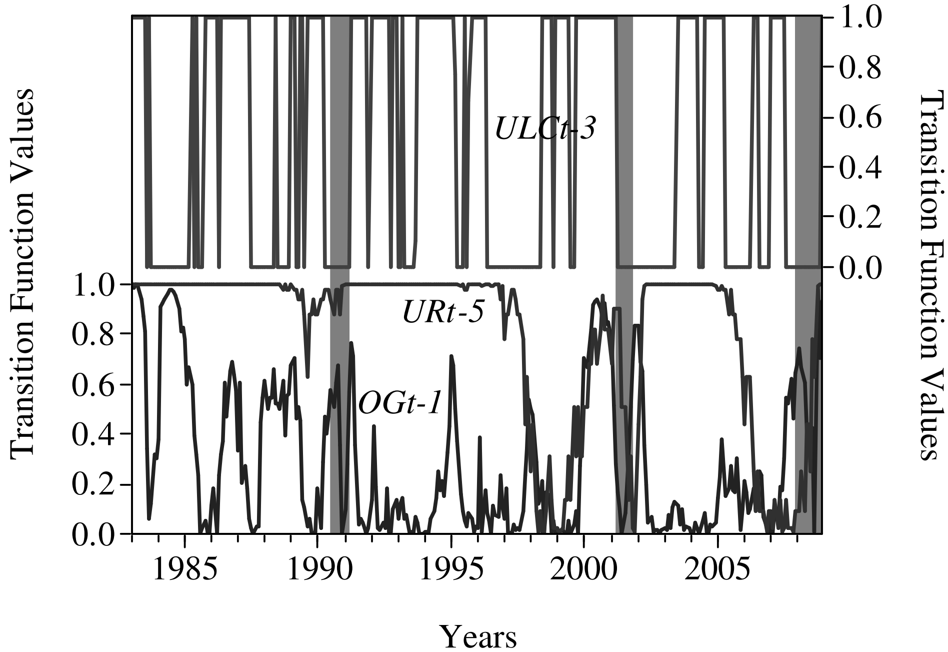
Figures

Figure 1
Estimated Transition Functions, 1983:01 to 2008:12



Notes: The transition functions are all on the same 0 to 1 scale. Separating them was done to add visual clarity. Gray bars are recessions as defined by the NBER. Functions are labeled by their respective transition variables.

Tables

Table 1
Unit Root Tests

Variable	$\pi - \pi^e$	*OG*	*ULC*	*UR*	*Z*
Selected Lag Length	1	6	10	6	12
T-Statistic	-5.56	-6.06	-5.62	-3.51	-3.82
P-Value	0.00	0.00	0.00	0.04	0.02

Notes: Since 12 lags was selected with AIC for the unit root test of *Z,* we increased the maximum to 13, and re-ran the results. A lag length of 12 was still selected.

Table 2

Estimates of Equation (1), 1983:01 to 2008:12

Parameter	*X*: *OG*	*ULC*	*UR*
α	-0.03	-0.03	0.39
	[0.17]	[0.23]	[0.02]
$\beta_{\pi(L)}$	0.89	0.89	1.00
	[0.00]	[0.00]	[0.00]
$\beta_{X(L)}$	0.06	0.05	-0.08
	[0.01]	[0.00]	[0.01]
$\beta_{Z(L)}$	-0.06	-0.05	-0.11
	[0.00]	[0.00]	[0.00]
NAIRU	0.51	0.56	5.18
Adjusted R^2	0.77	0.77	0.77
SSR	35.95	35.29	35.80

Notes: For β(L) parameters, reported coefficient is the sum of estimated lagged coefficients (11 lags based on AIC). Bracketed values are the p-values from a hypothesis test where the null is that the coefficient or coefficient sum is zero versus the alternative that it is not.

Table 3

Nonlinear Test Results

Explanatory Variable		*X*: *OG*	*ULC*	*UR*
π - π^e	Lag length	9	11	9
	LM Statistic	1.64	2.26	1.70
	P-Value	[0.00]	[0.00]	[0.00]
X	Lag length	1	3	5
	LM Statistic	2.41	2.31	2.19
	P-Value	[0.00]	[0.00]	[0.00]
Z	Lag length	1	1	4
	LM Statistic	1.94	2.26	1.97
	P-Value	[0.00]	[0.00]	[0.00]

Notes: The null hypothesis is linearity and the alternative hypothesis is nonlinearity. The Lagrange Multiplier test statistic is asymptotically F(132, 146) for each test.

Table 4

Exponential versus Logistic Test Results

Test	*3 Specifications (by Transition Variable S_{t-d})*		
	OG_{t-1}	ULC_{t-3}	UR_{t-5}
Even	2.38	1.90	1.92
	[0.00]	[0.00]	[0.00]
Odd	1.79	2.13	1.88
	[0.00]	[0.00]	[0.00]
Model Selected	ESTR	LSTR	ESTR

Notes: The test statistics are asymptotically distributed F(66, 146). P-values are in brackets.

Table 5

STR Model Estimates, 1983:01 to 2008:12

Coefficients	*3 Specifications (by Transition Variable S_{t-d})* OG_{t-1}	ULC_{t-3}	UR_{t-5}
	"Low" Regime		
δ	-0.03	-0.01	1.66
	[0.27]	[0.77]	[0.14]
$\lambda_\pi(L)$	0.89	0.97	0.79
	[0.00]	[0.00]	[0.00]
$\lambda_X(L)$	-0.02	0.03	-0.39
	[0.36]	[0.06]	[0.09]
$\lambda_Z(L)$	0.01	-0.16	0.10
	[0.01]	[0.00]	[0.00]
	"High" Regime		
$\delta + \mu$	-0.07	-0.01	0.46
	[0.20]	[0.94]	[0.02]
$\lambda_\pi(L) + \theta_\pi(L)$	0.99	0.88	1.01
	[0.00]	[0.00]	[0.00]
$\lambda_X(L) + \theta_X(L)$	0.09	0.04	-0.09
	[0.09]	[0.00]	[0.01]
$\lambda_Z(L) + \theta_Z(L)$	-0.07	0.01	-0.12
	[0.00]	[0.00]	[0.00]
γ	0.26	461.04	5.27
	[0.03]	[0.66]	[0.01]
c	-0.39	-0.09	4.57
	[0.00]	[0.00]	[0.00]
Adjusted R^2	0.80	0.79	0.78
S.E. of Regression	0.34	0.34	0.35
SSR	27.34	27.90	29.21
Log Likelihood	-62.91	-66.05	-73.23
Jarque-Bera	[0.00]	[0.41]	[0.00]
BPG Test	[0.89]	[0.77]	[0.00]
Serial Corr Test	[0.67]	[0.14]	[0.34]

Notes: Coefficient sums are presented based on regimes and p-values (in brackets) are for joint significance of coefficients where appropriate. The Jarque-Bera test is a test of the null of normal errors, the Breush-Pagan-Godrey (BPG) test is a test of the null of homoskedastic errors, and the Serial Corr test is a test of the null of no serial correlation in the error terms. Again, p-values are in brackets.