Threshold cointegration between inflation and US capacity utilization*

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Abstract

An analogue to the Phillips curve shows a positive relationship between inflation and capacity utilization. Some recent empirical work has shown that this relationship has broken down when using data after the mid 1980s. We empirically investigate this issue using several threshold error correction models. We find, in the long run, a 1% increase in the rate of inflation leads to approximately a 0.004% increase in capacity utilization. The asymmetric error correction structure shows that changes in capacity utilization show significant corrective measures only during booms while changes in inflation correct during both phases of the business cycle with the corrections being stronger during recessions. We also find that, in the short run, changes in the inflation rate do Granger cause capacity utilization while changes in capacity utilization do not Granger cause inflation. The Granger causality from inflation to capacity utilization can be interpreted as supporting recent calls made in the popular press by some economists that it may be desirable for the Fed to try to induce some inflation. The lack of Granger causality from capacity utilization to inflation casts doubt on the older view that capacity utilization could be a leading indicator for future inflation.

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1 Introduction

The popular Phillips Curve in traditional as well as New Keynesian models shows a short-run connection between inflation and output. This connection has led the Federal Reserve Bank (Fed) policy makers, who are on the lookout for inflation, to study the connection between capacity utilization and inflation with the expectation that capacity utilization may serve as a useful leading indicator for inflation.[1] Although some of the earlier papers seemed to find a connection, this connection appeared to drop off in the mid 1980s and several popular explanations for this changing relationship, including advancements in technology and globalization were put forward as possible explanations.[2] This decoupling can be understood anecdotally by noting the stable inflation that settled into the US economy beginning around 1983, which has come do be known as the Great Moderation, despite the economy still traveling through boom and recession episodes. In this paper, we use modern time series econometric methods to show that there continues to be both long run and short run linkages between capacity utilization and inflation.

Despite the mature nature of cointegration econometric methods, which are perfectly suited to studying short and long run connections between variables, there are few papers that have used these methods for investigating the potential long run connection between capacity utilization and inflation.[3][4] Several factors could account

[1] Among the numerous Federal Reserve Bank economists' papers are McElhattan (1978, 1985), Bauer (1990), P de Kock and Nadal-Vicens (1996), Corrado and Mattey (1997), Emery and Chang (1997), Dotsey and Stark (2004).

[2] Garner(1994), Gordon (1994), Cecchetti (1995) and Stock and Watson (1999), Corrado and Mattey (1997), Brayton, Roberts and Williams (1999). and Nahuis (2003) show that capacity utilization has significant positive relationship with inflation, thus predicting inflation better than the unemployment rate while Shapiro (1989) shows that high capacity utilization has a small, insignificant, and sometimes negative impact on prices. Finn (1995), Aiyagari (1994). Bansak, Morin, Starr (2007) examined the effects of technological change on capacity utilization, while Gamber and Hung (2001) and Dexterr, Levi, and Naultl (2005), show that international trade has a significant downward impact on US inflation, which might have obscured the relationship between capacity utilization and inflation in 1990s.

[3] The cointegration liturature dates back to Engle and Granger (1987) and has seen many important contributions over the years including Johansen (1988), Johansen and Juilius (1990), Hansen and Seo (2002) and of particular interest to this paper, Enders and Siklos (2001).

[4] One paper that does investigate cointegration is Mustafa and Rahman (1995) who use traditional cointegration methods. Unlike our results, they did not find a cointegration relationship between capacity utilization and inflation.

for this dearth of research, but perhaps one important one is how to undertake unit root tests on bounded series such as capacity utilization. Granger (2010) argues that although bounded time series cannot be integrated in the usual sense, in many theoretical and applied studies they are modeled as pure I(1) processes. He argues that if the bounded nature of a bounded process is not taken into account, the standard unit root test results will be biased.[5] Work by Cavaliere, (2005) and Cavaliere and Xu (2014) has shown this to be true, that conventional unit root tests tend to overreject the null hypothesis of a unit root, even asymptotically, and they are potentially unreliable in the presence of bounds.[6] A second important factor for the lack or research may be the inability of the traditional cointegration methods to handle changes in the nature of the relationship between variables.[7] Balke and Fomby (1997) argue that the tendency towards long-run equilibrium might not occur at each point of time as adjustments toward the long-run could be asymmetric. In this paper, we not only use the methods developed by Cavaliere and Xu (2014) to investigate unit roots, but we also use methods developed by Enders and Siklos (2001) to allow a switching structure in the relationship between the variables.

Using these methods, we show that both inflation and capacity utilization have unit roots and they are cointegrated. We show that the momentum threshold autoregression model (M-TAR) suggested by Enders and Siklos (2001) fits the data

[5] Examples of econometric studies with bounded time series variables are numerous. For example, in their influential paper Nelson and Plosser (1982) reject the unit root hypothesis of the U.S. unemployment rate and studies which link unemployment rates and other variables are quite commonplace. Several empirical models of the European Monetary System exchange rates have been specified by using (co-)integrated vector autoregressive (VAR) models without taking account of the presence unit root such as Anthony and MacDonald, (1998), Svensson (1993).

[6] Cavaliere (2005) explains how the concept of I(1) can coexist with the constraints of a bounded process. Further, Cavaliere and Xu. (2014) shows that the presence of bounds affects the standard unit root tests. Using the now popular, Monte Carlo methods to simulate correct critical values, they show that when bounds are taken into account, the Augmented Dickey Fuller tests is much less likely to reject the null of a unit root.

[7] For instance, asymmetric changes in the relationship between capacity utilization and inflation can be associated with the typical Keynesian story. According to this theory, a non-linearity in aggregate supply implies that when the overall resources in the economy are underutilized, firms can increase output without rising the price level because of sticky wages. But when rising aggregate demand pushes output beyond a certain threshold, the increasing marginal cost of resources causes prices to rise. Such an asymmetry was often found in the data from the 1970s and early 1980s where inflation was tame until capacity utilization exceeded a value around 82%.

best, thus showing that the cointegration structure requires a switching structure. Using a switching structure to estimate error correction models, we show that again asymmetries are present. The error correction models show both long run and short run dynamics are in play with the long run dynamics determined by the cointegration vector and the short run dynamics determined by the lagged differences of the two variables in the error correction structure. We can summarize some of the economic results as follows. The results are largely the same when measuring capacity utilization by either manufacturing capacity utilization or total capacity utilization. A 1% increase in the rate of inflation leads to approximately a 0.004% increase in capacity utilization in the long run.[8] The error correction structure shows that changes in capacity utilization show significant corrective measures only during booms while changes in inflation correct during both phases of the business cycle with the corrections being stronger during recessions. Changes in the inflation rate do Granger cause short term changes in capacity utilization while changes in capacity utilization do not Granger cause short term changes in inflation. The short term Granger causality from inflation to capacity utilization can be interpreted as supporting recent calls made in the popular press by some economists that it may be desirable for the Fed to try to induce some inflation in an effort to stimulate the economy.[9] The lack of short term Granger causality from capacity utilization to inflation casts doubt on the older view that capacity utilization could be a leading indicator for future inflation.

The rest of the paper is organized as follows. In Section 2 we describe various econometric techniques used in this paper and how they relate to the application we are investigating. Section 3 undertakes the econometric analysis and summarizes results of the various econometric steps. The conclusion is presented in Section 4.

[8] By 1% increase in the rate of inflation, we mean a calculation of $0.01\times$inflation, not $0.01+$inflation. We say approximately because we used two capacity utilization series, one of which implied an elasticity of 0.0041 and the other 0.0046.

[9] For example, on NPR on October 7^{th}, 2011, Ken Rogoff is quoted as saying, "They need to be willing, in fact actively pursue, letting inflation rise a bit more. That would encourage consumption. It would encourage investment...," while in The New York Times on October 29^{th}, 2011, Christina Romer said, "In the current situation, where nominal interest rates are constrained because they can't go below zero, a small increase in expected inflation could be helpful. It would lower real borrowing costs, and encourage spending on big-ticket items like cars, homes, and business equipment."

2 Empirical Methodology

Our empirical methodology follows methods used in Enders and Siklos (2001), who investigated threshold cointegration between short term and long term interest rates.[10] Our application investigates whether the log of capacity utilization, which we denote generically by c_t, is cointegrated with the log of the inflation rate which we denote by π_t.[11] The potential cointegrating relationship we investigate is given by

$$c_t = \alpha + \beta\pi_t + \mu_t \tag{1}$$

where α and β are parameters and μ_t is an error term. The cointegration methodology suggested by Engle and Granger (1987) and embraced by Enders and Siklos (2001) begins by using OLS to estimate (1), then recovering the residuals, which we denote by $\widehat{\mu}_t$, and then estimating a regression of the form

$$\Delta\widehat{\mu}_t = \rho\widehat{\mu}_{t-1} + \sum_{i=1}^{p} \gamma_i \Delta\widehat{\mu}_{t-k} + \varepsilon_t \tag{2}$$

where ρ and γ_i, for $i = 1, ..p$, are parameters and ε_t is an error term. In this regression, the lag length p is typically chosen by some type of information criterion so that the model is well specified and results in ε_t being white noise. Using the estimated parameter $\widehat{\rho}$ one tests the null $H_0 : \rho = 0$. If this is rejected, then one concludes that μ_t is stationary and thus c_t and π_t are cointegrated. There are some subtle aspects of testing hypotheses in this model, which are well known, and so we do not describe them in detail here. However, one important subtlety that is relevant for this paper is that the distribution for the test statistics, including the t-statistic for $H_0 : \rho = 0$ are not standard and need to be generated through Monte Carlo methods.

Enders and Siklos (2001) extend the early cointegration literature to investigate whether there is a threshold structure for the error term μ_t. For now we will describe

[10] The Threshold Autoregressive and Momentum Threshold Autoregressive models were first described by Tong (1983), Enders and Granger (1998).

[11] In Section 3 we investigate two types of capacity utilization including total and manufacturing, but to keep notation simple we denote them both with a single generic notation c_t.

their simplest extension, called a threshold aggressive (TAR) model, but later we will also discuss their so call momentum threshold autoregressive (M-TAR) model. The TAR model modifies (2) to include an asymmetry and is given by

$$\Delta\widehat{\mu}_t = I_t\rho_1\widehat{\mu}_{t-1} + (1 - I_t)\rho_2\widehat{\mu}_{t-1} + \sum_{i=1}^{p}\gamma_i\Delta\widehat{\mu}_{t-k} + \varepsilon_t \tag{3}$$

where ρ_1, ρ_2 and γ_i, for $i = 1, ..p$, are parameters and ε_t is an error term and I_t is an indicator function defined by

$$I_t = \begin{cases} 1 & \text{if} \quad \widehat{\mu}_{t-1} \geq 0 \\ 0 & \text{if} \quad \widehat{\mu}_{t-1} < 0 \end{cases}. \tag{4}$$

As in the Engle and Granger (1987) the lag length p is typically chosen by some type of information criterion so that the model is well specified and results in ε_t being white noise. Testing for cointegration is analogous to the earlier procedure and requires testing $H_0 : \rho_1 = \rho_2 = 0$. Enders and Siklos (2001) call this test statistic Φ, while a simpler statistic that looks at the largest of the two t-statistics for $H_0 : \rho_i = 0$, $i = 1, 2$,they call the t-max statistic. As with the Engle and Granger (1987) method, the test statistics do not have standard distributions and Enders and Siklos (2001) describe methods for generating proper critical values for them.

Once the presence of an asymmetric cointegration relationship is confirmed, one can investigate threshold vector error correction models (VECM) using $\widehat{\mu}_{t-1}$ by estimating

$$\Delta c_t = \alpha_c + \rho_{c,1}I_t\widehat{\mu}_{t-1} + \rho_{c,0}(1 - I_t)\widehat{\mu}_{t-1} + \sum_{i=1}^{p}\beta_{c,c,i}\Delta c_{t-i} + \sum_{i=1}^{p}\beta_{c,\pi,i}\Delta\pi_{t-i} + \varepsilon_{ct} \tag{5}$$

and

$$\Delta\pi_t = \alpha_\pi + \rho_{\pi,1}I_t\widehat{\mu}_{t-1} + \rho_{\pi,0}(1 - I_t)\widehat{\mu}_{t-1} + \sum_{i=1}^{p}\beta_{\pi,c,i}\Delta c_{t-i} + \sum_{i=1}^{p}\beta_{\pi,\pi,i}\Delta\pi_{t-i} + \varepsilon_{\pi t} \tag{6}$$

where α_j, $\rho_{j,1}$, $\rho_{j,0}$, $\beta_{j,c,i}$, and $\beta_{j,\pi,i}$ for $j = c, \pi$ and $i = 1, ...p$ are parameters to be estimated and ε_{jt}, for $j = c, \pi$, are error terms. In this specification, the subscripts make use of the following mnemonics. The first subscript indicates which equation the parameter or error term is from, the second subscript in the $\rho_{j,1}$and $\rho_{j,0}$ parameters indicates the value for I_t (e.g. 1 or 0), while the second and third subscripts attached to the lagged differenced variables correspond to the type of variable that is differenced (i.e. c or π) and the lag value for that differenced variable. In typical applications, the lag length p is chosen based on some sort of information criterion so that the model is well specified and results in the error terms being white noise.[12]

The various $\rho_{j,1}$, $\rho_{j,0}$ for $j = c, \pi$ are known as the speed of adjustment parameters. Like the speed of adjustment parameters in the basic Engle and Granger interpretations, they show how fast and in what direction the variables adjust to errors in the equilibrium relationship (1). However, here, the speed of adjustments not only depend on the equation of interest, but they also depend on whether the switching variable, $\widehat{\mu}_{t-1}$, is above or below the threshold 0. Also of note, is that Granger causality tests which examine the lead-lag relationship between changes in capacity utilization and changes in inflation rate can be investigated. The null hypothesis that changes in inflation do not Granger cause changes in capacity utilization can be formalized mathematically using a null given by

$$H_0 : \beta_{c,\pi,i} = 0 \;\; \text{for} \;\; i = 1, ...p, \tag{7}$$

whereas the null hypothesis that changes in capacity utilization does not Granger cause changes in inflation can be formalized mathematically using

$$H_0 : \beta_{\pi,c,i} = 0 \;\; \text{for} \;\; i = 1, ...p. \tag{8}$$

There are also various ways to extend the TAR model described above. One is an endogenous TAR model which redefines the switching indicator by

$$I_t = \begin{cases} 1 & \text{if} \;\; \widehat{\mu}_{t-1} \geq \tau \\ 0 & \text{if} \;\; \widehat{\mu}_{t-1} < \tau \end{cases} \tag{9}$$

[12] These empirical models make use of some standard notations such as α, β, ρ and ε in the different equations. However, these parameters and error terms do differ in the different equations and the subscripts should make things easy to see where each came from.

where τ is a threshold parameter to be estimated. A popular algorithm, due to Chan (1993), estimates τ jointly with the other parameters of the model by considering the middle 70% of the ordered observed values of $\widehat{\mu}_t$ (i.e. all the candidate $\widehat{\mu}_t$ values are ranked from highest to lowest and the top 15% and the bottom 15% are excluded from consideration) and then estimating the model for each of these possibilities. Among the many estimated models, the one with the lowest sum of squared residuals is then chosen as the best fitting model and its parameter estimates become the estimates used for the endogenous TAR model.

A second extension is known as a momentum threshold autoregressive (M-TAR) model. Here we also focus on an endogenous threshold version of this model, but in our analysis below we also consider one with an exogenous threshold with $\tau = 0$. This model has very similar properties to the TAR model, but shows more momentum during some portions of the correction process. The M-TAR model has only one small formal difference relative to the endogenous TAR model in that it defines the switching dummy by

$$I_t = \begin{cases} 1 & \text{if} \quad \Delta\widehat{\mu}_{t-1} \geq \tau \\ 0 & \text{if} \quad \Delta\widehat{\mu}_{t-1} < \tau \end{cases} \tag{10}$$

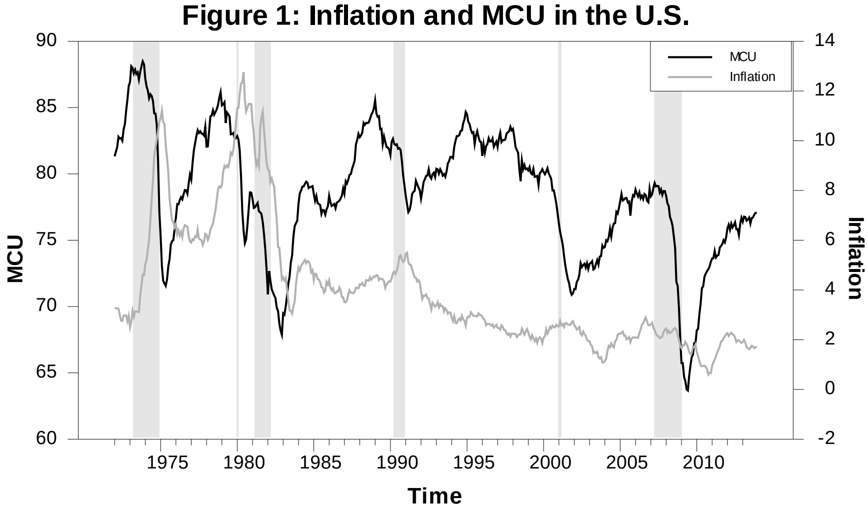
instead of by (9). For both of these alternative models, the mechanical details are the same as the TAR model as well as the error correction formulation.

3 Empirical results

Our empirical analysis uses monthly data for capacity utilization which is tabulated by the Federal Reserve Bank. We used two different measures for capacity utilization in order to investigate different cointegration possibilities. These include Total Capacity Utilization (TCU), which can be found at the Board of Governors of the Federal Reserve System website and is given by the series CAPUTL.B50001.S and Manufacturing units Capacity Utilization (MCU), which can be found at the same website and is given by the series CAPUTL.B00004.S. We used the full set of available data for each series, but they did have slightly initial dates. For TCU we used the data interval 1967:1 to 2013:12, while for MCU we used 1972:1. to 2013:12. We computed the annual inflation rate using the usual formula from what is often referred to as the core CPI series, or more specifically, the Consumer Price Index for All Urban Consumers: All Items Less Food and Energy Inflation Series (CPILFESL) which was downloaded from the Federal Reserve Bank of St. Louis Economic Data (FRED) base. We use the core inflation rate in part because of it is a prefered measure of inflation by the Fed, and in part because studies, such as Finn (1996), have shown that fuel prices have a negative impact on capacity utilization. The CPI data was available for all the dates that the two capacity utilization data were available, so in the results presented below the intervals of time correspond to the two capacity utilization intervals.

Figure 1 shows a plot of MCU and inflation over the period from 1972:1. to 2013:12, with the shaded areas representing the NBER recessionary periods.[13] The figure shows the moderating inflation rate after 1983 which has confounded some of the work trying to link capacity utilization and inflation. The figure also shows that MCU tends to decline sharply during recessions and slowly increase during recoveries and boom periods.

Figure 1: Inflation and MCU in the U.S.



[13] A plot of TCU would almost precisely sit on top of the plot of MCU and to avoid confusion, we have left it off.

The first step in a cointegration investigation is to investigate whether the series are individually integrated. We ran a battery of different unit root tests to investigate this issue and Table 1 summarizes some of these results. The table is organized into three vertical panels, with the leftmost panel showing results using inflation data, the middle panel showing results for manufacturing capacity utilization and the rightmost panel showing the results for total capacity utilization as indicated in the first row of the table.[14] Each vertical panel has three horizontal subpanels which report results for the Augmented Dickey-Fuller tests (ADF), Phillips-Perron (PP) tests and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests. These are among the most popular unit root tests, with the ADF and PP tests using a null of nonstationarity and the KPSS using a null of stationarity. For each series, models with different deterministic variables were run, with one including both a deterministic trend and a constant term, one with only a constant term and one without either a deterministic trend or a constant. These three alternatives are marked in the second row of the table and summarized with mnemonic column notations of Trend, for models with a deterministic time trend and a constant, Cons, for models with just a constant and None for models with neither a deterministic trend or a constant. For the ADF tests, a preliminary analysis to determine the number of lags on the differenced terms using the Schwartz Bayesian Criterion (BIC) was undertaken and as indicated in the table, the inflation series best fit with 13 lagged differenced terms while both the manufacturing capacity utilization and total capacity utilization series best fit with 4 lagged difference terms.

The first row with numbers shows the value of the t-statistic for the ADF test. In particular, the ADF test statistic for the inflation series in a model with a deterministic time trend and a constant was -3.16, for a model with just a constant term was -1.89 and for a model with no deterministic trend or constant term was -1.24. As noted at the bottom of the table, we use a convention of including asterisks to indicate significance levels, with one asterisk indicating significance at the 10% level,

[14] The data interval in this table for inflation was 1967:1 to 2013:12.

two asterisk indicating significance at the 5% level and three asterisks indicating significance at the 1% level. This convention is also used in Tables 3 and 4 below. For the ADF tests, we used the conventional critical values in applying the significance notations. As can be seen in the table, all of the inflation models could not reject the null of nonstationarity using the ADF tests. Table 1 also provides the 5% critical values directly below the coefficients in parenthesis terms, which may be a useful reference for reinforcing ones thinking about these tests. So as indicated in the table, the conventional 5% critical values for the ADF test on inflation for the model with deterministic trend and a constant is -3.41, for the model with only a constant is -2.86, and for the model without a deterministic trend or constant is -1.95.

For the two capacity utilization series, we report the conventional ADF critical values in the second line and the Cavaliere and Xu (2014) bounded series adjusted critical values in the third line for the model in which there is a constant term. Based on arguments in Cavaliere (2005), Granger (2010) and Cavaliere and Xu (2014), conventional unit root critical values are inappropriate for bounded series. Furthermore, Cavaliere (2005) and Cavaliere and Xu (2014) argue that conventional unit root critical values are inappropriate for series which are influenced by policy control exercise. Both of these rationals play a role with capacity utilization. In particular, capacity utilization indices are by construction bounded between 0 and 100. In addition, policy makers indirectly target capacity utilization since capacity utilization is the analogue of labor unemployment which they directly target. In other words, by targeting labor unemployment directly, policy makers are also targeting capacity utilization indirectly and this binds capacity utilization even more than the simple 0 and 100 values. Based on these arguments, in the presence of construction bounds as well as policy bounds, the conventional unit root test statistics are biased in favor of rejecting the null hypothesis of stationarity. This issue is perfectly illustrated here, where we see that using the conventional ADF critical values we reject the null hypothesis of nonstationarity, but when using bounded series adjusted critical values we fail to reject nonstationarity for the models with constant terms.[15]

The next horizontal panel shows the results for the PP test, which is a popular alternative to the ADF test. Unlike the ADF test, there are only two variations of the PP. In particular, there is no version that does not have a deterministic trend and a constant. This panel is organized in a similar fashion to the ADF test panel, with the t-statistics reported in the first row of the panel, the conventional 5% critical values in the second row of the panel and the bounded series adjusted critical values reported in the third row. This panel also shows that we can never reject the null hypothesis of nonstationarity for any of the series using either the conventional critical values or the bounded series adjusted critical values.

The last horizontal panel shows the results for the KPSS test, which is a popular alternative to conventional unit root tests because it has a null that the series is stationary. Like the PP test, there is no version of the test for a model without a constant. Like the other two panels, the first row of the panel shows the test statistic results while the second row shows the 5% critical values for the test. Unlike the other two panels, there are no Cavaliere and Xu (2014) bounded series adjusted critical values. For all three series, the KPSS tests are always rejected at the 5% level which shows consistency with the other tests in that this test also concludes that all three series are nonstationary.

Taken as a whole, these results show strong evidence that the series are nonstationary. Although the ADF critical values for the two capacity utilization variables indicated these series were stationary, when using what we consider to be the more reliable Cavaliere and Xu (2014) critical values, the ADF tests show these series to be nonstationary. This nonstationary result is further confirmed using the PP and KPSS tests. Since the series are nonstationary, this means there is a chance they can be cointegrated. We now turn to that analysis.

[15] Cavaliere and Xu's (2014) simulation based tests are applicable when bounds are known. Based on their arguments a reasonable range for the bounds can often be inferred from historical observations. We choose the lower and upper bounds of the capacity utilization rate, respectively, at 60 percent and 90 percent as the historical data shows that the capacity utilization rate never lies beyond this range. See also Herwatz and Xu (2008) for further details.

Table 1: Unit root tests

Inflation			MCU			TCU		
Trend	Cons	None	Trend	Cons	None	Trend	Cons	None
Augmented Dickey-Fuller - H_0: Nonstationarity								
	Lags = 13			Lags = 4			Lags =4	
-3.16	-1.89	-1.24	-3.87**	-3.53**	-0.22	-4.39**	-3.78**	-0.23
(-3.41)	(-2.86)	(-1.95)	(-3.41)	(-2.86)	(-1.95)	(-3.41)	(-2.86)	(-1.95)
				(-3.71)			(-3.83)	
Phillips-Perron Test - H_0: Nonstationarity								
-3.25	-2.02		-2.62	-2.40		-3.03	-2.85	
(-3.42)	(-2.87)		(-3.42)	(-2.87)		(-3.42)	(-2.87)	
				(-3.46)			(-3.71)	
KPSS Test -H_0: Stationarity								
0.21**	2.35***		0.43***	2.19***		0.36***	3.07***	
(0.15)	(0.46)		(0.15)	(0.46)		(0.15)	(0.46)	

Notes: Values in parenthesis are 5% critical values. For Tables 2-4, ***, ** and * denote the significance at the 1%, 5% and 10% level respectively. ADF tests significance are based on conventional (nonbounded series adjusted) critical values.

To investigate cointegration we now estimate (1) for each of the capacity utilization series and recover the residuals for unit root analysis and later error correction estimation. The estimated long-run relationships are given by

$$c_{M,t} = \underset{(0.0049)}{4.35} + \underset{(0.0009)}{0.0041}\pi_t + \widehat{\mu}_{M,t} \tag{11}$$

and

$$c_{T,t} = \underset{(0.0049)}{4.37} + \underset{(0.0009)}{0.0046}\pi_t + \widehat{\mu}_{T,t} \tag{12}$$

where $c_{M,t}$ and $c_{T,t}$ indicate the manufacturing and total capacity utilization variables respectively, $\widehat{\mu}_{M,t}$ and $\widehat{\mu}_{T,t}$ are the residuals from each equation and a mnemonic convention of denoting the manufacturing capacity utilization variables with initial subscripts of M and total capacity utilization variables with initial subscripts of T has been used. The standard errors for the estimated coefficients are presented directly below the parameter estimates in parenthesis. These regression results show highly significant parameter estimates in both equations as well as very comparable values between the two equations. The estimated slope coefficients show the elasticity of capacity utilization with respect to inflation and indicate that if the inflation rate goes up by 1% then MCU will go up by 0.0041%, and TCU will go up by 0.0046%.

Also of interest are the Regression Error Specification Tests (RESET) which test the null hypothesis of linearity against the alternative hypothesis of nonlinearity. In particular, if the residuals of the linear cointegrated variables are independent, they should not be correlated with the regressors used in the estimating equation or with the fitted values. Thus a regression of the residuals on these values should not be statistically significant. For the MCU data, the RESET test has a value of 9.90 which is highly significant, while for the TCU data, the RESET test has a value of 8.26 which is also highly significant. Because the RESET test has a general alternative hypothesis, the test is helpful in determining whether a nonlinear model is appropriate but not in determining the nature of the nonlinearity. Even so, these results can be interpreted as providing evidence of a nonlinearity in the cointegration relationship between capacity utilization and inflation as well as evidence that the error correction term has a nonlinear relationship for the adjustment towards long-run equilibrium.

We now turn to investigating the structure for the cointegration relationship. Table 2 summarizes the estimation results for several different models described earlier. The table is organized into two vertical panels, with the left panel summarizing the results when using the residuals from (11), which is the model using the MCU data, and the right panel summarizing the results when using the residuals from (12), which is the model using the TCU data. Within each panel, four models are investigated. The first is the standard structure given by (2), which we denote by E-G since this is the form used in the original Engle and Granger approach. The next three are various forms of the TAR models, with the second column in each panel corresponding to the model given by (3) and (4), the third column corresponding to the model given by (3) and (10) with $\tau = 0$, and the fourth column corresponding to the model given by (3) and (10) with τ estimated based on an algorithm suggested by Chan (1993). One clarification about the structure of the table is useful to note. In particular, for the basic model given by (2), which we denote E-G, there is only one ρ term with no subscript. To save space, for this model, we listed this estimated parameter in the same row as the ρ_1 terms in the various TAR models. Another important detail in interpreting the table is to note that the number of lagged differences used in the models differs for MCU and TCU. For MCU, we used 4 lags, which is the number of lags suggested when using either the Akike Information Criterion (AIC) or the BIC to chose the lag length for the standard E-G model while for TCU, we used 5 lags because this was the number suggested from the AIC and BIC in the standard E-G model. We went ahead and used the same lag lengths for the various TAR models in part to maintain comparability across models.

In addition to the parameter coefficient estimates, Table 2 reports AIC values, and various cointegration test statistics. For the standard E-G model, the relevant statistic is the ADF hypothesis $H_0 : \rho = 0$ while for the TAR and M-TAR models the relevant statistics are the Φ and $t - Max$ statistics suggested by Enders and Siklos (2001). The Φ statistic tests the null $H_0 : \rho_1 = \rho_2 = 0$ while the $t - Max$ statistic is the largest t-statistic among the two nulls of $H_0 : \rho_1 = 0$ and $H_0 : \rho_2 = 0$. As pointed out by Enders and Siklos (2001), one advantage of the $t - Max$ statistic is that it never rejects the null of nonstationarity of the residual (and thus concludes there is cointegration of the variables) when either ρ_1 or ρ_2 are positive, while the Φ statistic could reject the null even when one of the ρ_i values are positive.[16] However they argue the Φ statistic does have improved power and thus they place more faith in its value.[17]

[16] The desirability of having both ρ_i values negative is motivated by Petrucelli and Woolford (1984), who showed that necessary and sufficient conditions for stationarity are $\rho_1 < 0$, $\rho_2 < 0$ and $(1 + \rho_1)(1 + \rho_2) < 1$.

[17] This can be seen on page 169 of Enders and Siklos (2001) where they say, "However, as will be shown, the phi statistic is quite useful because it can have substantially more power than the t-Max

Table 2: Testing for threshold cointegration between inflation and capacity utilization

	MCU				TCU			
	E-G	TAR	M-TAR	M-TAR	E-G	TAR	M-TAR	M-TAR
Threshold		$\tau = 0$	$\tau = 0$	$\tau = -0.0029$		$\tau = 0$	$\tau = 0$	$\tau = -0.0053$
ρ_1	-0.021***	-0.016	-0.023***	-0.030***	-0.024***	-0.020***	-0.024***	-0.031***
	(0.006)	(0.0086)	(0.008)	(0.007)	(0.006)	(0.009)	(0.008)	(0.007)
ρ_2		-0.024***	-0.019***	-0.001		-0.027***	-0.025***	-0.001
		(0.007)	(0.008)	(0.001)		(0.008)	(0.008)	(0.012)
γ_1	0.256***	0.255***	0.255***	0.246***	0.256***	0.255***	0.256***	0.238***
	(0.044)	(0.044)	(0.045)	(0.04)	(0.042)	(0.042)	(0.042)	(0.043)
γ_2	0.242***	0.242***	0.239***	0.224***	0.149***	0.149***	0.149***	0.141***
	(0.046)	(0.046)	(0.046)	(0.046)	(0.044)	(0.044)	(0.044)	(0.045)
γ_3	0.136***	0.137***	0.133***	0.127	0.153***	0.153***	0.153***	0.142***
	(0.045)	(0.046)	(0.046)	(0.046)	(0.044)	(0.044)	(0.044)	(0.044)
γ_4	0.027	0.029	0.026	0.019	0.113**	0.115**	0.114**	0.110**
	(0.045)	(0.045)	(0.045)	(0.045)	(0.044)	(0.044)	(0.044)	(0.044)
γ_5					-0.025	-0.023	-0.025	-0.034
					(0.043)	(0.043)	(0.043)	(0.043)
AIC	-1810.49	-1808.92	-1808.61	-1814.25	-2030.20	-2028.62	-2028.21	-2033.32
$H_0 : \rho = 0$	-3.79**				-4.16**			
Φ		7.39**	7.23**	10.11**		8.86**	8.64**	11.26***
$t - Max$		-1.95**	-2.28**	-0.16		-2.27**	-2.92**	-0.06
$H_0 : \rho_1 = \rho_2$		0.43	0.13	5.73**		0.41	0.01	5.08**

Focusing on the panel with the MCU results we can see the following. The E-G model has an estimate $\rho = -0.20$ which implies a t-statistic of -3.79. This statistic exceeds the 5% critical value of 1.96 and implies that we reject the null of nonstationarity of the residual series, which is typically interpreted to mean the residuals are stationary and thus the variables in the first step regression are cointegrated.[18] Next focusing on the TAR model we see that both of the ρ_i values are negative, as required for stationarity, and the preferred Φ statistic also rejects the null of nonstationarity

statistic." It can also be seen in Table 7 of their paper, where they do not even report the $t - Max$ statistic values.

[18] Here we use the conventionally Engle and Granger cointegration adjusted ADF statistics rather than a bounded series ADF statistic. We do this because, even though it is reasonable that c_t is bounded, because π_t is not, any linear combination of the two may not be bounded, so the Cavaliere and Xu (2014) adjustment is not needed.

of the residuals and thus implies the first step regression variables are cointegrated.[19] This model also has $t - Max$ statistic of -1.95 which is significant at 5% level and implies the variables are cointegrated. Recognizing this pattern, we see that two M-TAR models have ρ_i values with the appropriate signs and Φ statistics that point to cointegration of the variables in the first step regression, however, one difference is that the $t - Max$ is significant only for the M-TAR model with the threshold exogenously specified with $\tau = 0$. While the $t - Max$ result for the endogenous M-TAR does not point to cointegration, we take some comfort in the guidance from Enders and Siklos (2001) who note that the Φ statistics have better power and are the preferred statistic.[20] Overall, these results all show that the variables in the first step regression are cointegrated. Next shifting attention to the TCU side of the table we again see that all the models are consistent in that they show that there is cointegration for the first step regression variables.

The next task is to decide which of these candidate models fit the best. One criterion is to use the AIC values which are reported toward the bottom of the table. This statistic picks the M-TAR with endogenous threshold for both capacity utilization measures. Another result that also provides insight into making this choice is to investigate the null that the two ρ_i coefficients are equal in the various TAR and M-TAR models. This test is reported in the last line of the table and shows the M-TAR model with endogenous threshold rejects the null of symmetric adjustment for both types of capacity utilization variables, while the TAR and the constrained threshold M-TAR model do not. This indicates that an endogenous threshold does a better job of fitting the data.

To interpret this asymmetric result, several background details must be recognized first. First note that (1) implies

[19] The critical values for the Φ statisitics and the $t - Max$ statistics can be found in Enders-Siklo (2001).

[20] This preference for the Φ statistics can also be seen in the literature. For instance, Shen, Chen and Chen (2007) only mention the Φ statistic results and do not mention the $t - Max$ results.

$$\mu_t = c_t - \alpha - \beta\pi_t,$$

which implies that the state $\Delta\mu_t$ is above the threshold when either Δc_t is sufficiently positive or $\Delta\pi_t$ is sufficiently negative or some some combination of the two and conversely $\Delta\mu_t$ is below the threshold when either Δc_t is sufficiently negative or $\Delta\pi_t$ is sufficiently positive or some combination. Because the relative sizes of Δc_t and $\Delta\pi_t$ impact whether $\Delta\mu_t$ is above or below the threshold, it is useful to start by looking at Figure 1. There it can be seen that the most rapid changes in either direction for c_t and π_t occur in c_t when the economy is in recession. Figure 1 shows that c_t falls at a very high rate in recessions which will produce a large negative Δc_t which overwhelms any values for $\Delta\pi_t$. Figures 2a and 2b plots both μ_t and $\Delta\mu_t$ for the two capacity utilization series and it shows this to be true. In particular, it shows that negative values for $\Delta\mu_t$ tend to occur in recessions and positive values in booms. Next note that ρ_1 corresponds to above threshold $\Delta\mu_t$ and ρ_2 corresponds to below threshold $\Delta\mu_t$. Also note that because ρ_1 is more negative than ρ_2, it implies that when the economy is in the ρ_1 state, there is less persistence than when the economy is in the ρ_2 state. Taken together, the larger value of ρ_1 indicates that there is less persistence in booms than in recessions. Although this may seem counterintuitive to general business cycle facts, that intuition would be wrong, because that intuition is not appropriate for M-TAR models. What is important in the M-TAR is the momentum, so here, the momentum of the recession is so violent that it sustains itself, i.e. it is highly persistent, until the economic bottom is reached and the economy then switches out of the negative state and recovers. But the recovery is more uneven in terms of momentum, with some minor switches out of the positive momentum state during the recovery, which can be interpreted as lower persistence.[21]

Figure 2a: Cointegration residuals: MCU

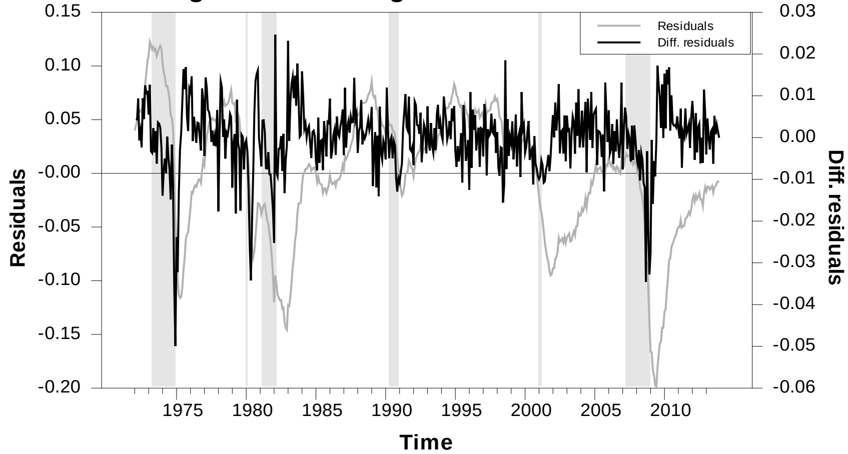
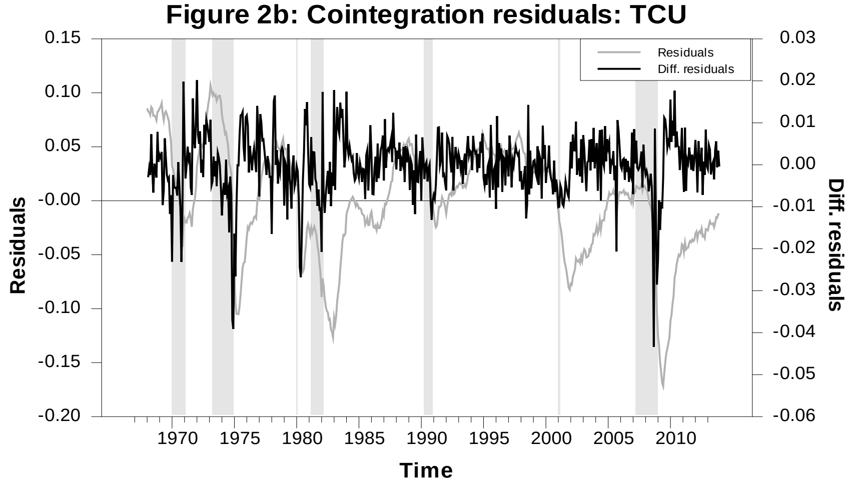


Figure 2b: Cointegration residuals: TCU



Because we found that the variables are cointegrated with asymmetric adjustments of the error correction terms, investigating the VECM models given by (5) and (6) using the endogenous threshold M-TAR model is justified. We used two

[21] A useful alternative exercise is to look at the TAR model which does not have the momentum interpretation. So in the TAR models, positive values of μ_t tend to occur when c_t is large and π_t is small which tend to be booms. Looking at the coefficients we see the more negative coefficient is associated with ρ_2 or the recession periods and this more negative coefficient indicates less persistence during the recession.

lags in the error correction term, which is justified by the AIC. Table 3 shows the results of this threshold VECM estimation. As in the Table 2, this table is organized into two vertical panels. The first column shows a list of the variables in the VECM equations (5) and (6), while the second and third columns show the estimated coefficients for the variables in (5) and (6) respectively using the MCU data, and the fourth and fifth columns showing the estimated coefficients for the variables in (5) and (6) respectively using the TCU data. Coefficients on Δc_{t-k} and $\Delta\pi_{t-k}$ represent the short run adjustments, while the coefficients on $I_t\widehat{\mu}_{t-1}$ and $(1-I_t)\widehat{\mu}_{t-1}$ represent the speed of adjustment for the error in the cointegrating vector under the two states of the word. In addition, the t-statistics for each estimated parameter are listed below the estimates.

Interpreting the error correction coefficients in Table 3 is a bit more complicated than a TAR model, because each variable in each row consists of an error term $\widehat{\mu}_{t-1}$ and an indicator variable which is defined from $\Delta\widehat{\mu}_{t-1}$. As we noted above, negative values of $\Delta\widehat{\mu}_{t-1}$ are associated with recessions, so we next need to consider the error term $\widehat{\mu}_{t-1}$. As can be seen in Figures 2a and 2b, negative values are generally associated with recessions too, but not to the extent that $\Delta\widehat{\mu}_{t-1}$ is, with $\widehat{\mu}_{t-1}$also covering part of the initial phase of the recovery when c_t is still relatively low. For simplicity, it is may be easier to think of negative $\widehat{\mu}_{t-1}$ as associated with low c_t rather than simply associated with recessions even though the exact details are a bit more nuanced. Looking at the coefficients on $I_t\widehat{\mu}_{t-1}$, we see that for Δc_t they are significantly negative and for $\Delta\pi_t$ they are significantly positive. So economically we could say that during booms ($I_t = 1$), positive values of $\widehat{\mu}_{t-1}$, which are associated with high c_t, result in Δc_t correcting downward (or c_t decreasing). Similarly, we would say that during booms ($I_t = 1$), positive values of $\widehat{\mu}_{t-1}$, which are associated with high values of c_t, result in $\Delta\pi_t$ correcting upward (or π_t as increasing). Looking at the coefficients on $(1-I_t)\widehat{\mu}_{t-1}$, we see that for Δc_t they are insignificantly positive and for $\Delta\pi_t$ they are significantly positive. So economically we could say that during recessions ($I_t = 0$), there is no significant impact on the rate at which Δc_t corrects, but positive values of $\widehat{\mu}_{t-1}$, which are associated with high c_t, result in $\Delta\pi_t$ correcting upward (or π_t is increasing). This last sentence may seem counterintuitive, but that is simply because we were looking at positive values of $\widehat{\mu}_{t-1}$. Alternatively, we can make the same statements with a negative value of $\widehat{\mu}_{t-1}$ and say that during recessions ($I_t = 0$), there is no significant impact on the rate at which Δc_t corrects, but negative values of $\widehat{\mu}_{t-1}$, which are associated with low c_t, result in $\Delta\pi_t$ correcting downward (or π_t decreasing). Furthermore, it is possible to put some asymmetric interpretations on the error corrections. So for instance, one could say that during booms, firms are more willing to slow capacity utilization toward its long run than to increase capacity utilization toward its long run during recessions. Their reluctance to increase capacity utilization during recessions could be due to the violent nature of recessions and the unease about where the bottom might be. On the other hand, the relative sizes of the error correction coefficients for $\Delta\pi_t$ show that the speed of the correction in $\Delta\pi_t$ is larger in recessions ($I_t = 0$), than the speed of the correction during booms ($I_t = 1$). Put differently, inflation slows much more quickly during recessions than it speeds up during booms.

Table 3: Estimated results of the threshold VECM

	MCU		TCU	
Dependent Variables	Δc_t	$\Delta\pi_t$	Δc_t	$\Delta\pi_t$
$I_t\widehat{\mu}_{t-1}$	-0.015**	0.541**	-0.015**	0.651***
	(0.007)	(0.213)	(0.007)	(0.234)
$(1-I_t)\widehat{\mu}_{t-1}$	0.003	1.033***	0.004	1.518***
	(0.010)	(0.290)	(0.012)	(0.384)
Δc_{t-1}	0.026***	-1.922	0.272***	-1.608
	(0.044)	(1.313)	(0.043)	(1.415)
Δc_{t-2}	0.276***	2.17*	0.194***	1.279
	(0.044)	(1.298)	(0.043)	(1.421)
$\Delta\pi_{t-1}$	-0.001	0.250***	-0.001	0.244***
	(0.001)	(0.044)	(0.001)	(0.042)
$\Delta\pi_{t-2}$	-0.004***	0.215***	-0.003**	0.193***
	(0.001)	(0.044)	(0.001)	(0.042)
$\overline{R}^2$	0.25	0.24	0.19	0.22
F-statistic	5.28**	1.86	3.77**	0.83

Notes: Constant terms are not reported.

The error correction models given by (5) and (6) can also shed light on some recent economic commentary. In particular, following the financial crisis and the recession it precipitated, some economists have suggest that raising inflation expectations might help speed up the recovery. To investigate this hypothesis, we conducted Granger causality tests to see if changes in inflation can Granger cause changes in capacity utilization. In addition we also investigated whether changes in capacity utilization can Granger cause changes in inflation. These hypothesis were described formally in (7) and (8) where $p = 2$ for this application. The last row of Table 3 shows the value of the F-statistics for these tests in the different models. These tests show that we are able to reject the null given by (7) at the 5% level for either of the capacity utilization models with F-statistics of 5.28 in the manufacturing capacity utilization model and 3.77 in the total capacity utilization model. These results show that changes in inflation do Granger cause changes in capacity utilization and confirm the economic speculations that inducing changes in inflation will result in changes in capacity utilization. On the other hand, these tests also show that we are unable to reject the null given by (8) at even the 10% level that changes in capacity utilization cause changes in inflation with F-statistics of 1.86 and 0.83. Intuitively this means that changes in capacity utilization do not Granger cause changes in inflation.

4 Conclusion

In this paper, we investigate the short term and long term connections between capacity utilization and inflation. Contrary to much of the recent literature, which has shown that the relationship between capacity utilization and inflation has broken down since mid 1980s, we show that both series continue to have short term and long term connections. We argue that part of the reason for these different results is the theoretical nature of capacity utilization which entails a switching structure and by using the M-TAR model developed by Enders and Siklos (2001) we are better able to econometrically model the data and capture the nature of the short run and long run connections. We find, in the long run, a 1% increase in the rate of inflation leads to approximately a 0.004% increase in capacity utilization. The error correction structure shows that changes in capacity utilization show significant corrective measures only during booms while changes in inflation correct during both phases of the business cycle with the corrections being stronger during recessions. Asymmetric interpretations on these error corrections are as follows. During booms, firms are more willing to slow capacity utilization toward its long run than to increase capacity utilization toward its long run during recessions. Their reluctance to increase capacity utilization during recessions could be due to the violent nature of recessions and the unease about where the bottom might be. On the other hand, the relative sizes of the error correction coefficients for inflation show that the speed of the correction is larger in recessions, than the speed of the correction during booms. Put differently, inflation slows much more quickly during recessions than it speeds up during booms.

We also find that in the short run, changes in the inflation rate do Granger cause short term changes in capacity utilization while changes in capacity utilization do not Granger cause short term changes in inflation. The short term Granger causality from inflation to capacity utilization can be interpreted as supporting recent calls made in the popular press by some economists that it may be desirable for the Fed to try to induce some inflation in an effort to stimulate the economy. The lack of short term Granger causality from capacity utilization to inflation casts doubt on the older view that capacity utilization could be a leading indicator for future inflation.

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