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Keywords: Business cycles, stall speed, Markov switching

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Does US GDP stall?

Wai-Yip Alex Ho and James Yetman[1]

Abstract

Low positive GDP growth has been interpreted as evidence that the economy may be "stalling", implying that low growth is a strong predictor of future recessions. We examine the empirical evidence for stalling based on kernel density estimates, probit estimates and Markov switching models.

Whether we find evidence for stalling or not depends crucially on how a stall is defined. If we define a stall as a low but positive growth rate, then there is no evidence of stalling in US GDP. Low growth is as likely to be followed by higher growth as by a recession. In contrast, if we define a stall as a decline in the growth rate of the economy to below some threshold, we find evidence for stalling.

We also discuss the merits of each of the definitions of stalling, and limitations in using aeronautical analogies for discussing the business cycle.

Keywords: Business cycles, stall speed, Markov switching

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Contents

Introduction 1
1. Data and kernel density evidence 2
2. Probit estimates 4
   2.1 Stall as low growth rate 4
   2.2 Stall as declining growth rate 6
3. Markov switching evidence 8
   3.1 Stall as low growth rate 8
   3.2 Stall as declining growth rate 12
Conclusions 13
Appendix 1: Full Markov switching estimation results 14
Appendix 2: Full out-of-sample forecasting mean square error results 16

Fear that the US economy is like an aircraft – and has a "stall speed" at which it will suddenly lose traction and tumble – has been an important influence on both investors and the US Federal Reserve as they fret about a deluge of bad economic data.

("'Stall speed' fears sway investors and Fed", *Financial Times*, 11 August 2011)

Introduction

A drop in GDP growth rates to low but still positive levels has been interpreted by analysts and commentators as evidence that the economy may be "stalling". In mechanical terms, a stall implies a discrete deterioration in behaviour. An aircraft stalls when the angle of attack of its wings increases to the point where lift begins to decrease. Flight controls become less responsive, increasing the risk of entering a spin. The aircraft may experience buffeting and lose altitude rapidly. Once an aircraft enters a stall, correct pilot inputs – to reduce the angle of attack and increase power – are necessary before stable flight can resume. Even then, the passengers will experience a turbulent ride.

Applying the analogy of a stall to the macroeconomy, a stalling economy would be one that is growing too slowly for the normal drivers of growth to function, leading to a sharp deterioration in economic performance. Perhaps low growth causes confidence to fall, so that firms cut back on investment and consumers reduce spending. Or, with the economy growing more slowly than its potential output, the rising quantity of unused resources becomes destabilising.

There is more than one way of applying the concept of stalling to the data. Nalewaik (2011) models a stalling economy as one in which the growth rate of the economy is too low to sustain normal growth and which thereby slips into recession. Sheets and Sockin (2012) suggest an alternative explanation: a stalling economy is one in which the growth rate of the economy has slowed below some threshold so that normal growth is no longer sustained. In principle, these applications of the concept of stalling to the macroeconomy sound very similar. In practice, they have very different implications. Using the Nalewaik assumption, we show that there is no evidence of stalling in US GDP. Low positive growth rates commonly occur both before the US economy enters recessions and immediately after it exits. Taking both these sets of observations together, low positive growth is about as likely to be followed by higher growth as a recession. In contrast, if we focus on periods in which low positive growth follows periods of higher growth, as in the Sheets and Sockin definition, then stalling helps to predict future recessions. We make our arguments using three complementary methods:

- First, we look at kernel density estimates to outline the basic arguments surrounding stalling.
- Second, we estimate a probit model to see if low positive growth helps to predict future recessions.
- Third, we estimate Markov switching models to see if we can identify a separate state of the economy that corresponds to a stall.

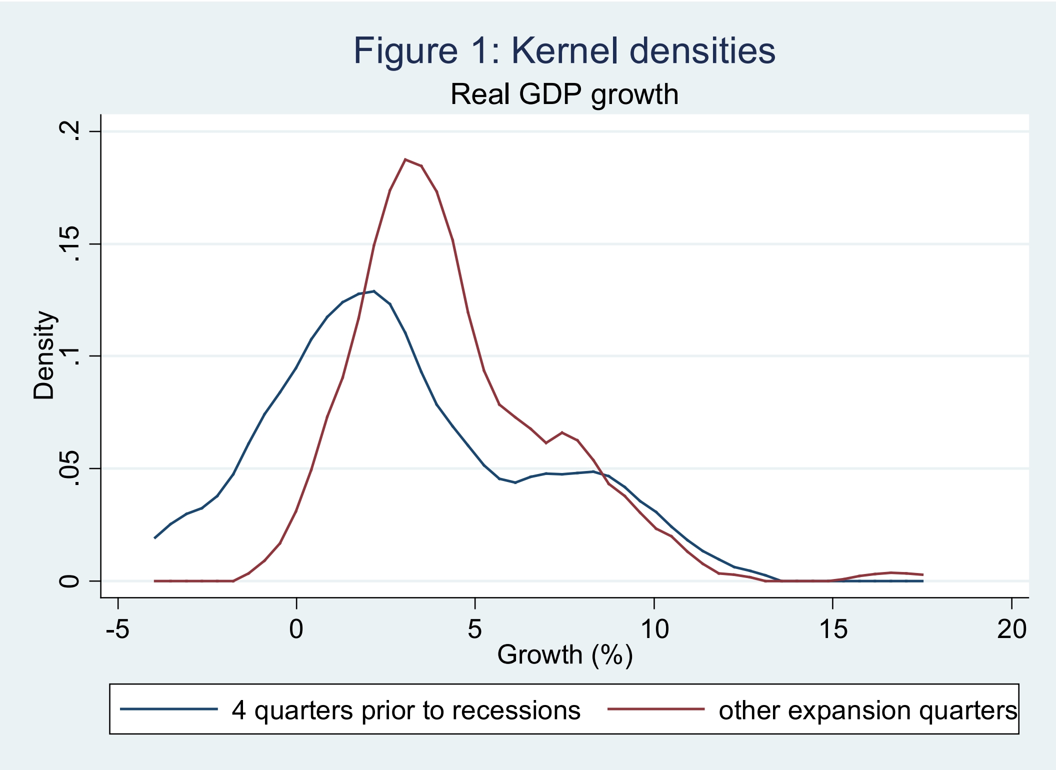
In Section 1, we describe our data and explore the kernel density evidence. Section 2 contains probit estimates. Markov switching models are discussed in Section 3, before we conclude.

1. Data and kernel density evidence

Our data are quarterly real GDP growth (at annual rates, seasonally adjusted) downloaded from the Federal Reserve Bank of St Louis's FRED database. The sample period is from Q4 1959 to Q2 2010, as of 30 September 2010. NBER business cycle dates are used to identify recessions, with a quarter classified as being in recession if any of its three months follows a peak and precedes the subsequent trough.[2]

Kernel density estimates provide a convenient way of graphically representing the key arguments of this paper. Figure 1 contains two lines: the estimated densities of GDP growth in the four quarters prior to recessions, and in all other periods with positive GDP growth.[3] The former is left-skewed relative to the latter, and illustrates that recessions tend to be preceded by periods of low growth. That is, conditional on the economy entering a recession in the coming four quarters, the economy is likely to be experiencing lower than normal growth today.

However, this empirical regularity could result either because the economy stalls prior to entering recessions or because GDP is inertial. In the stall interpretation, low growth in the periods before a recession reflects a change in the underlying relationships in the economy that bring about the recession. In the inertia interpretation, output is slowing due to a combination of persistent shocks and their propagation through the economy. Its inertia alone implies that low growth will generally be observed before negative growth.



Low growth tends to precede recessions …

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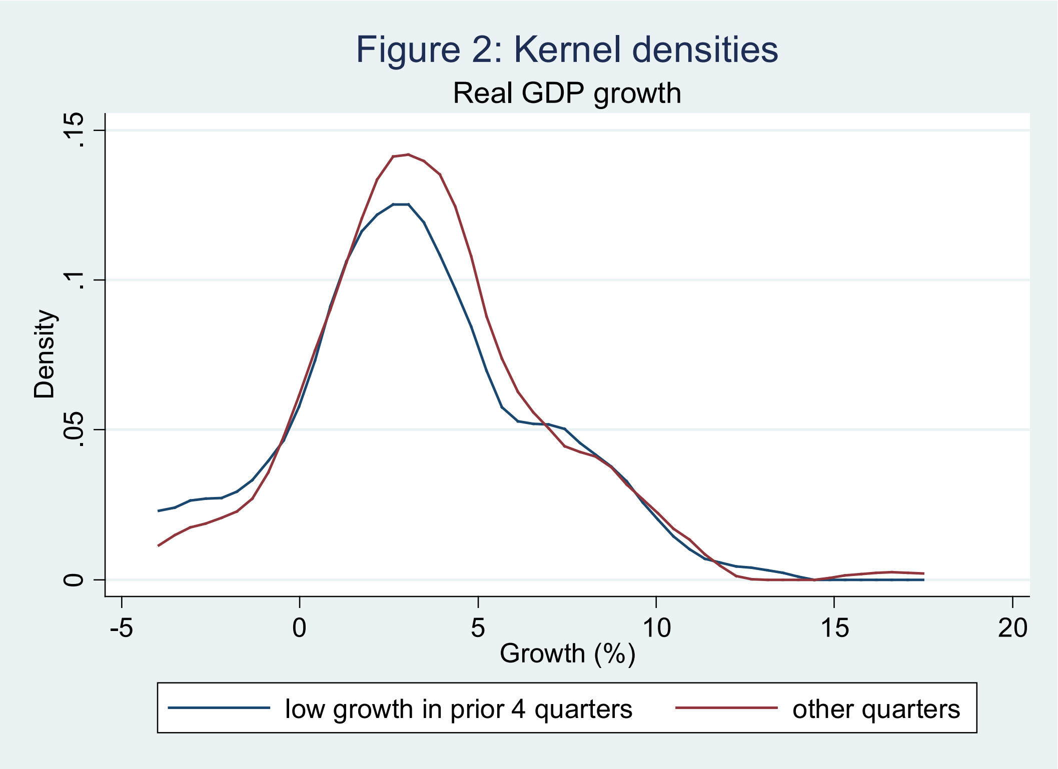
2 For example, in the case of NBER recession dates December 1969 to November 1970, December 1969 is defined as the peak of the cycle, so Q4 1969 is not classed as a recession quarter. In contrast, for the recession from November 1973 to March 1975, the peak of the cycle is in November 1973. Since December 1973 is after the peak, Q4 1973 is classed as a recession quarter.

3 These estimates are based on the Epanechnikov kernel and the default bandwidth setting in Stata.

To reduce the role of inertia, we need to reverse the conditionality to ask: conditional on an economy experiencing low growth, is it likely to enter a recession in the coming periods?

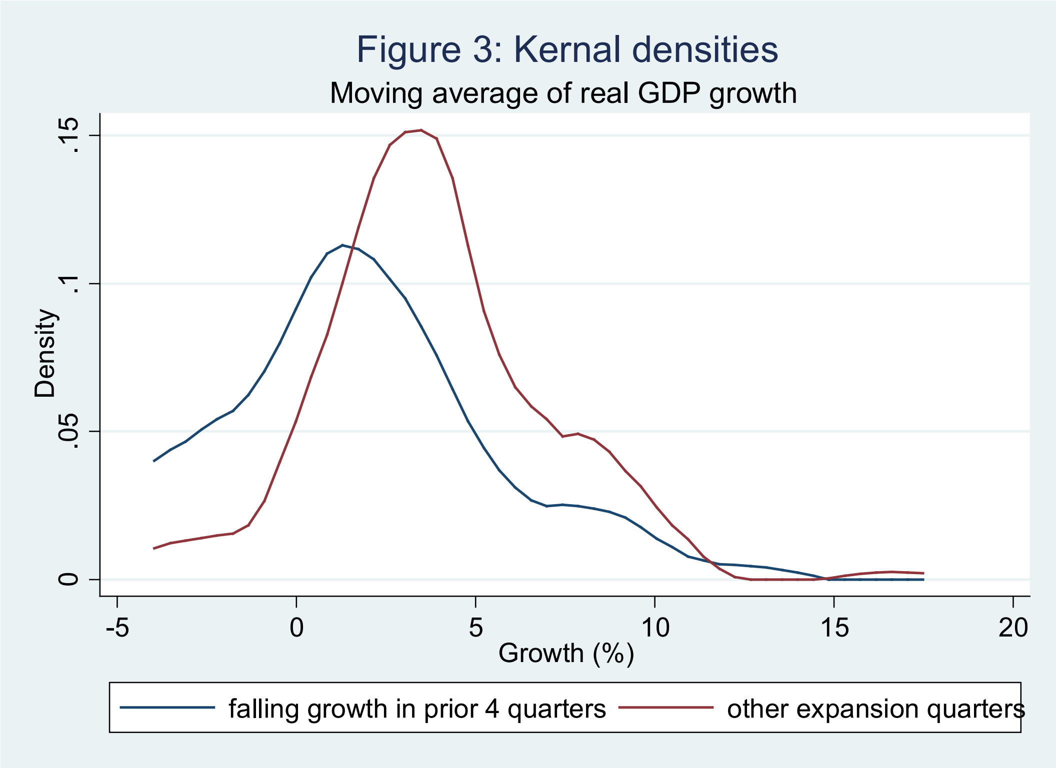
Figure 2 provides one answer to this question. We divide the sample into periods in which the economy experienced low growth in at least one of the preceding four quarters (defined as between 0 and 1% at annual rates, as in Nalewaik (2011)), and other periods. If low growth represents a stalling economy, then the kernel density in periods that have been preceded by low growth should be left-skewed relative to other periods. However, there is little difference between the two kernel densities. The distribution of output growth is almost identical whether the economy has experienced low growth in the preceding four periods or not. And the positive tail is almost identical across the two distributions as well, indicating that low-growth periods are no less likely to presage high future growth than other periods.



… but low growth does not predict a recession….

Figure 3 provides an alternative answer to the question of whether slow growth precedes recession. We divide the sample into periods in which the economy's growth rate declined, with the four-quarter moving average of GDP growth falling below 1.5% in one of the preceding four quarters (as in Sheets and Sockin (2012)), and other growth periods. If falling growth rates represent a stalling economy, then the kernel density following periods in which the growth rate fell below some threshold should be left-skewed relative to other growth periods. Indeed, that is what we find. Suitably parameterised, a slowdown in GDP growth rates may be a useful predictor of a future recession.

Comparing the results in Figure 2 with those in Figure 3, it is clear that evidence for stalling depends critically on how a stall is defined. Low positive growth by itself may not be a good predictor of a future recession; in contrast, a recent slowdown in growth rates to low levels may be a good predictor of a future recession.



… although a slow-down in growth does predict a recession.

2. Probit estimates

Graphs of kernel densities provide simple, visual evidence of the importance of the definition of stalling. However, they do not allow us to identify the role of inertia in driving the above results. To rectify this, we consider formal tests, based on probit estimates.

2.1 Stall as low growth rate

We first define a stall as a low growth rate in one of the preceding four quarters, as in Figure 2 above. We then estimate a univariate probit model of US recessions, regressing a binary variable that takes the value 1 during recessions, and 0 otherwise, on two lags of quarterly real GDP growth (additional lags are not statistically significant) and a dummy variable that takes the value 1 if any of the previous four quarters had growth between 0 and 1%.

The results are given in Table 1. They indicate that lower growth in either of the previous two quarters increases the likelihood of the economy entering a recession, and the estimates are highly significant. But when we include a stall variable, our coefficient has the right sign (indicating that a recession is more likely if the economy has experienced slow growth – between 0 and 1% in the previous four quarters), but it is far from statistically significant.[4]

As a further exercise, we check how including a stall variable affects the ability of the model to correctly identify the phase of the business cycle in-sample.

[4] The evidence is even weaker with alternative cutoffs for stall states. Indeed, if stalls are defined as growth of 0.0–0.5%, 0.0–1.5% or 0.0–2.0%, then the coefficient on the stall variable has the incorrect sign.

Table 1

Probit regression results

Dependent variable: US recession		Observations = 201	
		Wald $\chi^2(3) = 27.65$ (0.00)	
		Log pseudo likelihood = –58.61	
		Pseudo $R^2 = 0.37$	
Variable	**Coefficient**	**Standard error**	***p*-value**
Real GDP growth (*t*–1)	–0.27	0.07	0.00
Real GDP growth (*t*–2)	–0.11	0.04	0.01
Low growth between (*t*–1) and (*t*–4)	0.20	0.27	0.46
Intercept	–0.28	0.21	0.19

Figure 4 plots the percentage of correct in-sample predictions of the business cycle phase (vertical axis) across two versions of the probit model: including or excluding the stall dummy. The horizontal axis contains the threshold probability: a threshold of 40% means that the model is said to predict a recession if the fitted value of the regression exceeds 0.40, and growth otherwise.

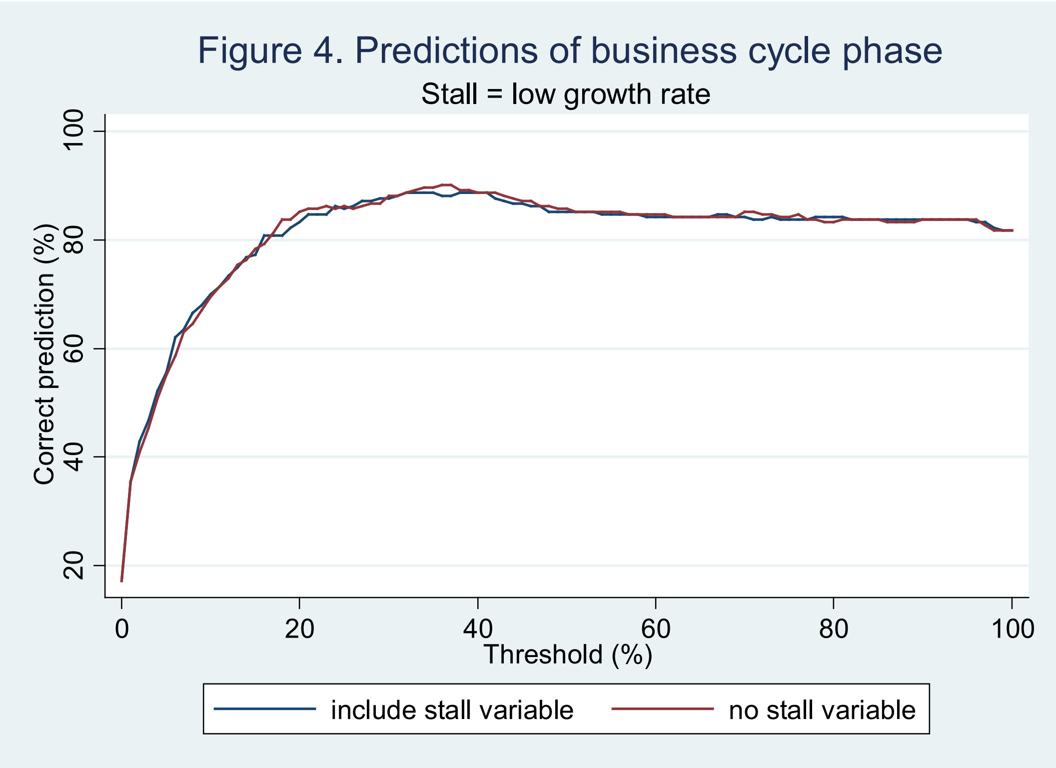


Figure 4. Predictions of business cycle phase

There is very little difference between the predictive ability of the two models. With a low threshold, implying that recessions tend to be over-predicted, adding the stall variable slightly improves the likelihood of correctly predicting the phase of the business cycle; however, in this range, almost half of the non-recessionary periods are wrongly labelled as recessionary. In contrast, if instead we focus on the threshold at which the highest number of periods is correctly identified, around 40%, then adding the stall variable results in a slight deterioration in the number of correctly predicted periods. We obtain similar results if we focus on the ability of the model to correctly predict only recessions, or growth periods.

These results reinforce the view that adding a stall variable, defined as a low growth rate, adds little to our ability to identify recessions, even in-sample. While the growth rate enters significantly in our regressions, a decline in the growth rate from (say) 3% to 2% has a similar effect on the probability of a future recession as a decline from 1.5% to 0.5%. These results suggest that there is no non-linear deterioration at low growth rates, contrary to what a "stall" would imply. In the same way as recessions are less likely following higher growth, recessions are more likely following low growth.

2.2 Stall as declining growth rate

We next redefine a stall as a fall in the growth rate in one of the preceding four quarters, such that the four-quarter moving average falls below 1.5%, as in Figure 3. We again estimate a univariate probit model of US recessions, including two lags of quarterly real GDP growth (additional lags are not statistically significant) and a dummy variable that takes the value 1 if the economy stalled in one of the previous four quarters and 0 otherwise.

Table 2

Probit regression results

Dependent variable: US recession		Observations = 201	
		Wald $\chi^2(3)$ = 36.92 (0.00)	
		Log pseudo likelihood = –55.74	
		Pseudo R^2 = 0.40	
Variable	**Coefficient**	**Standard error**	***p*-value**
Real GDP growth (*t*–1)	–0.23	0.07	0.00
Real GDP growth (*t*–2)	–0.07	0.05	0.13
Decline in growth between (*t*–1) and (*t*–4)	0.77	0.31	0.01
Intercept	–0.59	0.25	0.02

The results are given in Table 2. In contrast with the previous results, the stall variable is now highly significant: a decline in the growth rate to below 1.5% in one of the previous four periods is related to a much higher probability of the US entering a recession.[5]

We also check how including a stall variable affects the ability of the model to correctly identify the phase of the business cycle in-sample.

[5] These results are robust to using lags on the four-quarter moving average of the growth rate (instead of lags on the growth rate) or using a cutoff of 2.0% instead of 1.5%. However, the results are insignificant with a cutoff of 0.5% or 1.0%.

Figure 5. Predictions of business cycle phase
Stall = decline in growth rate

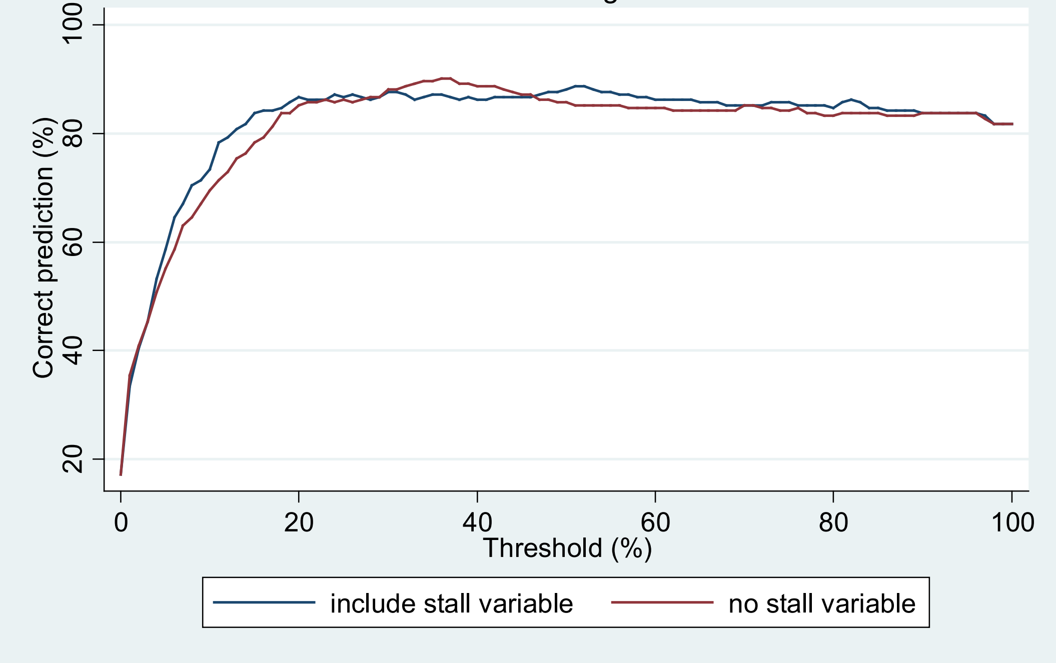
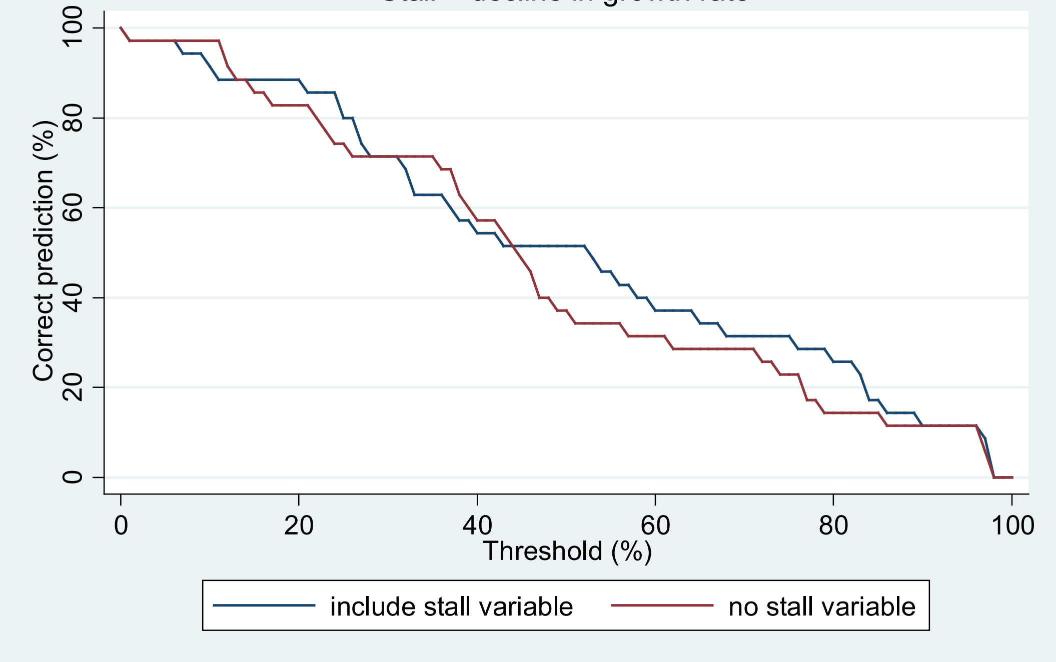


Figure 5 plots the percentage of correct in-sample predictions of the business cycle phase. Surprisingly, there is not a large difference between the two models. However, if we only focus on recession periods (Figure 6), the new model does a much better job of correctly identifying recessions over a significant portion of the range, in particular if we define the model as predicting a recession when the fitted value of the model lies between 0.45 and 0.85.

Figure 6. Predictions of recessions
Stall = decline in growth rate



3. Markov switching evidence

A more comprehensive framework for examining the role of different states of the economy in explaining the business cycle is to estimate Markov switching models. In principle, if stalling is an important characterisation of a phase of the business cycle, we should be able to identify a separate state of the business cycle that corresponds to a stall state, appropriately defined, and a high probability of transitioning to a recession state.

3.1 Stall as low growth rate

We first consider versions of the model where a stall state is defined as a low growth rate state. Nalewaik (2011) estimated a three-state Markov switching model similar to the one we use here.[6] He illustrated the quantitative value of including a low-growth state in the model to improve forecasts of future recessions, at least in the case where variables in addition to real GDP are included in the analysis. For example, in a version of his model that includes both real GDI and real GDP, hitting the low-growth state significantly increases the likelihood of experiencing a recession in the following period. (In fact, in his estimates, all occurrences of the low-growth state are followed by recessions.)

His model includes the following features. To help identify the stall state, he does not allow the economy to jump directly from the highest-growth state to the lowest-growth state. Additionally, his estimates of the lowest-growth state (both the mean growth rate and the probability that a recession period will be followed by another recession period) are calibrated, based on observations for actual NBER recession dates, rather than estimated.[7]

Our estimation differs from that of Nalewaik in two important ways. First, we focus solely on GDP, given that this is the most commonly used measure of the business cycle. And second, we consider versions of the model where the parameters associated with the recession state are estimated, as well as calibrated.[8]

Our estimated model takes the following form:

$$y_t = \mu(s) + \sigma\varepsilon_t, \quad \varepsilon_t \sim N(0,1),$$

where the state is defined by s, μ is the mean growth rate in state s, and the transition matrix is given by:

$$\begin{pmatrix} \Pr(s_t = 1) \\ \Pr(s_t = 2) \\ \Pr(s_t = 3) \end{pmatrix} = \begin{pmatrix} p_{11} & p_{21} & 1 - p_{32} - p_{33} \\ 1 - p_{11} & p_{22} & p_{32} \\ 0 & 1 - p_{21} - p_{22} & p_{33} \end{pmatrix} \begin{pmatrix} \Pr(s_{t-1} = 1) \\ \Pr(s_{t-1} = 2) \\ \Pr(s_{t-1} = 3) \end{pmatrix},$$

6 See also Layton and Smith (2000). For an alternative approach based on Multiple Regime Smooth Transition AutoRegressive (MRSTAR) models, see van Dijk and Franses (1999).

7 Nalewaik (2011) calibrates the average growth rate during recessions (μ_3), and the probability that one recessionary quarter will be followed by another (p_{33}), to match those found in actual recession data. We follow this approach in some versions of our estimates reported in Appendix 1 (these are labelled "calibrated recession state").

8 We also examined versions of the model that include a lagged dependent variable, but this is insignificant in most variants of the model.

where the states are ordered from highest to lowest growth. Results from our base specification are given in Table 3.[9]

We can identify three separate states. However, none corresponds to a stall state. State 3 is clearly a recession state, with significantly negative growth, that occurs in about 15% of all periods. State 2 is a normal growth state, occurring in about 70% of all periods, with an average growth rate close to the historical mean at 3.2%. And state 1 is a very high-growth state, with average growth rates of 8%, that occurs approximately 15% of the time.

Table 3

Markov switching regression results

	μ_1	μ_2	μ_3	σ^2	**Likelihood**	p_{11}	p_{22}	p_{33}	p_{21}	p_{32}
Estimate	7.99	2.85	–3.39	4.71	–526.37	0.54	0.84	0.55	0.10	0.35
Std error	0.56	0.26	0.60	0.32		0.12	0.05	0.14	0.04	0.14

We also consider a range of different possible specifications to check the robustness of our results.[10] In particular, we impose $p_{21} = p_{23}$ (so that the middle state leads to state 1 and state 3 with equal probability) and $p_{21} = 0$ (so that the middle state can only lead to a recession state) and consider two- and four-state versions of the model.

Across all three-state models, we can identify three separate states, but in no cases does one of the states correspond to a stall. Rather, a more reasonable interpretation of the three states is surge, normal growth and recession. Interestingly, in one of the two-state specifications, we do not separately identify a recession state, but just surge and normal growth states. If there is a third state of the economy that stands out in this version of the model, it is not stalls but surges.

We also consider a four-state Markov switching model to see if we can identify a fourth state in addition to surge, normal growth and recession that is consistent with stalling. In the case of calibrated recession estimates, we cannot identify any fourth state. In the case of estimated recession estimates, we can identify a low-growth state (Model 9 in Appendix 1), but the estimates are not consistent with a stall state. Ordering the states from 1 to 4 representing high growth, normal growth, slow growth and recession, we find that low growth commonly follows recessions ($p_{43} = 0.62$) and high growth is as likely to follow low growth as a recession is ($p_{31} = p_{34} = 0.21$). In contrast to our estimates, if the low-growth state were a stall state, we would expect p_{43} to be small and p_{34} to be large relative to p_{31}.

As a final test, and to guard against over-fitting in-sample, we also construct out-of-sample predictions of real GDP growth from a range of different models to see which better predict real GDP growth. We start by estimating each Markov switching model from Q4 1959 to Q2 1981. We then construct out-of-sample forecasts for the following quarter. We subsequently add one more observation and repeat the estimation and forecasting until the end of the sample. Finally, we calculate the mean square error of the forecasts for each model and each time period. The full results are given in Appendix 2.

9 Standard errors are calculated using the information matrix (estimated with the outer-product of the first derivative matrix of the likelihood function). In the case where we include calibrated coefficients, their standard errors are based on the first derivative of the likelihood function.

10 For results across different model specifications, see Appendix 1.

We find that adding a third state nearly always improves forecast performance compared with a two-state model. Forecast performance materially deteriorates if we impose $p_{21} = p_{23}$, implying that normal growth is as likely to be followed by a surge as by a recession. In contrast, it generally improves if we impose $p_{21} = 0$, implying that surge states never follow periods of normal growth, but only follow recessions.

Our Markov switching estimates and forecasts suggest that, along with periods of normal growth and recessions, there is a third state of the economy that corresponds to surges. Burns and Mitchell (1946) first discussed such high-growth periods, and argued that they commonly follow recessions. Friedman (1969, 1993) talked of recessions as periods when output is temporarily "plucked" below sustainable levels, after which high growth rates return the economy to its original path. Kim and Nelson (1999) and Kim and Murray (2002) decomposed the business cycle into transitory and permanent components and found that the transitory component explains most of the variation during recessions, consistent with Friedman's plucking model.[11] Sichel (1994) provided an explanation for this pattern. Based on estimated linear models of GDP growth, he found that inventory investment was a plausible candidate to explain the transitions between the three states over the business cycle.

Figure 7
Smoothed state probabilities
Three-state, estimated recession state

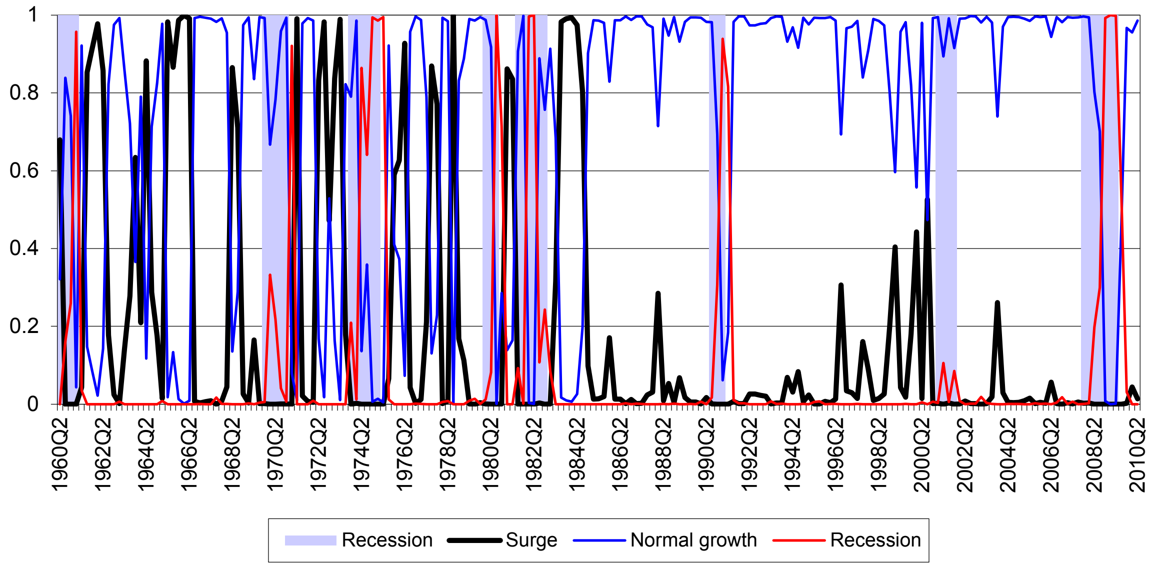
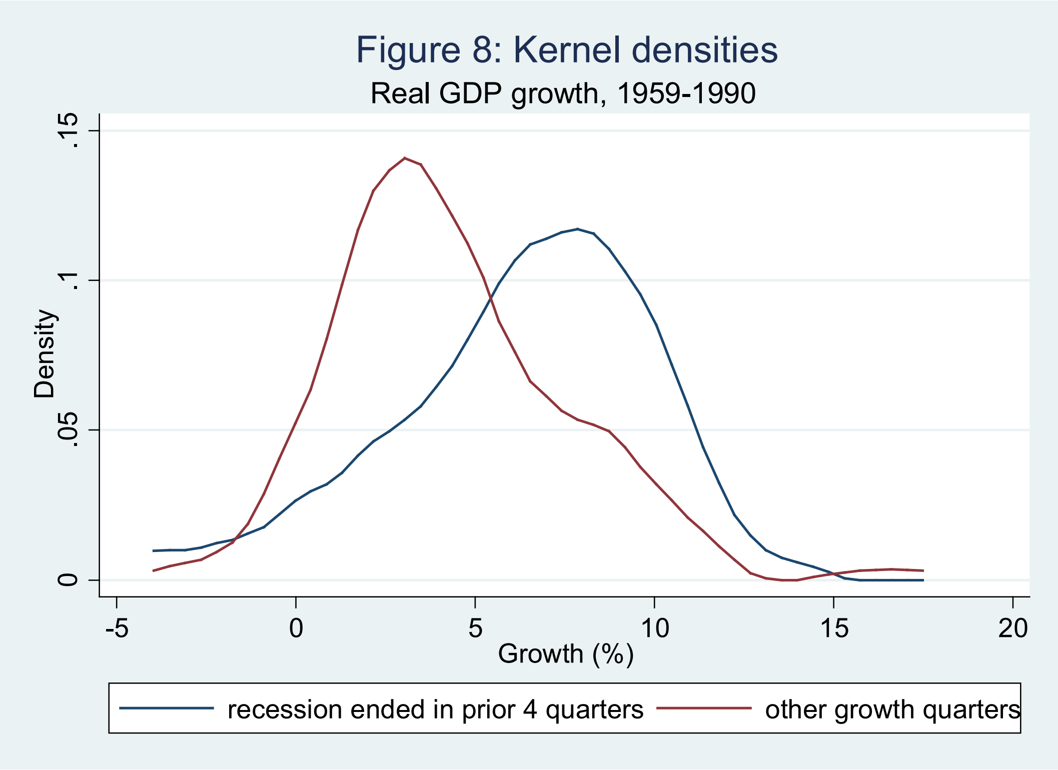


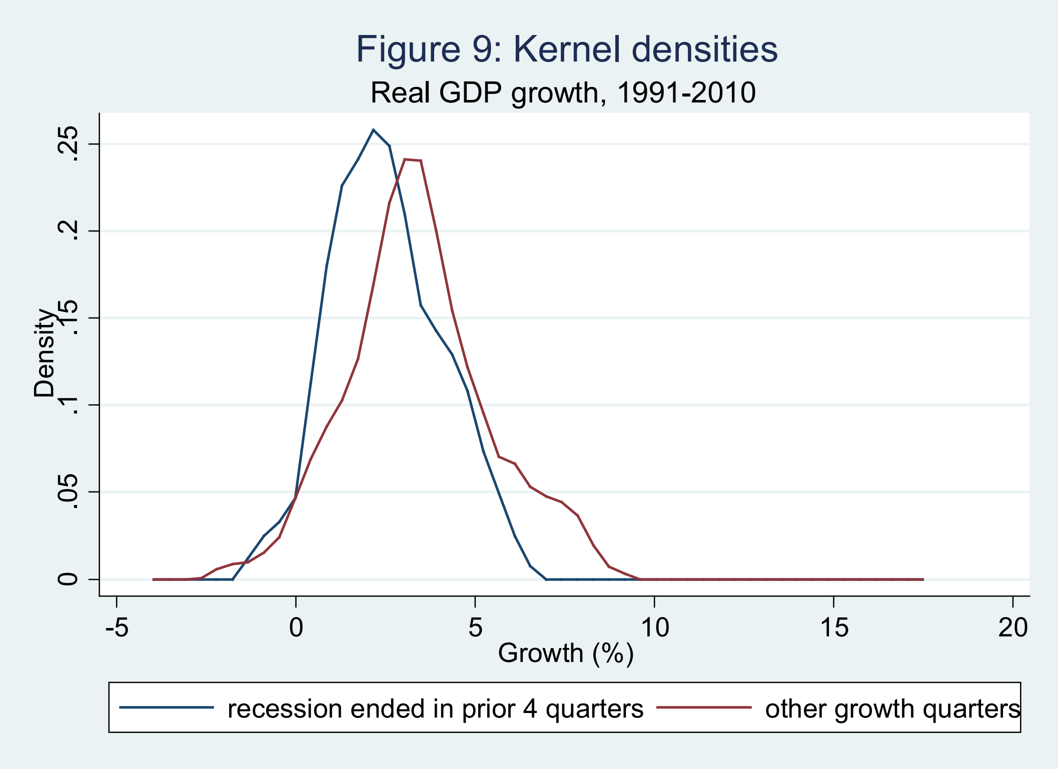
Figure 7 plots the smoothed probabilities of being in each state implied by our base model estimates (reported in Table 3). The probability of being in the surge state (solid black line) is typically strongest in our estimates either directly following recessions, consistent with Friedman's plucking model, or for brief periods during growth phases of the business cycle.

However, there is little evidence of any surge states in our estimates since the 1980s, suggesting that the plucking model is no longer empirically relevant. Kernel density estimates accord with this view. Figure 8 plots the kernel densities for the periods following recessions

[11] Kim and Nelson (1999) worked within a univariate Markov regime switching model that focused on *GDP* and *unemployment* separately. Kim and Murray (2002) worked within a multivariate Markov regime switching model that focused on *industrial production*, *personal income (less transfer payments)*, *manufacturing and trade sales* and *civilian labour force employed in non-agriculture* jointly.

and other growth periods over the 1959–90 subsample, and Figure 9 for 1991–2010. In the earlier period, growth rates following recessions are clearly right-skewed relative to other growth periods. During the later period, by contrast, GDP growth is slightly weaker, on average, in the periods following recession compared with other growth periods.





Kim and Murray (2002) noted that the recovery from the 1990–91 recession differed from earlier recoveries in that it was not followed by a period of high growth. Camacho et al (2011) report similar results for the two most recent recessions and argue that this may be explained by changes in inventory management brought about by improvements in information and communications technology. Bordo and Haubrich (2012) argue that the lack of a strong recovery following the 1990–91 and 2007–09 recessions reflected low residential investment. Regardless of the explanation, the economy no longer appears to return to its original output path following a recession, in contrast to the prediction of Friedman's plucking model.

3.2 Stall as declining growth rate

We now consider whether our Markov switching estimates can be shown to be supportive of a stall state, using the alternative definition from Sheets and Sockin (2012). To do so, we start with our previously estimated four-state model. We then add an additional low-growth state, dividing up low-growth periods into those that follow higher growth and those following recessions. Our states then correspond to (surge, normal growth, low growth following a surge or normal growth, low growth following a recession, recession), with the transition matrix given by:

$$\begin{pmatrix} \Pr(s_t=1) \\ \Pr(s_t=2) \\ \Pr(s_t=3) \\ \Pr(s_t=4) \\ \Pr(s_t=5) \end{pmatrix} = \begin{pmatrix} p_{11} & p_{21} & p_{31} & p_{41} & p_{51} \\ p_{12} & p_{22} & p_{32} & p_{42} & p_{52} \\ p_{13} & p_{23} & p_{33} & 0 & 0 \\ 0 & 0 & 0 & p_{44} & p_{54} \\ 0 & p_{25} & p_{35} & p_{45} & p_{55} \end{pmatrix} \begin{pmatrix} \Pr(s_{t-1}=1) \\ \Pr(s_{t-2}=2) \\ \Pr(s_{t-3}=3) \\ \Pr(s_{t-4}=4) \\ \Pr(s_{t-5}=5) \end{pmatrix}.$$

We then calibrate the means in each of the states to those estimated previously in the four-state case (Model 9 in Appendix 1), and estimate the transition probabilities between each of the states.

Table 4

Model with Sheets and Sockin (2012) stall state; calibrated means

	μ_1	μ_2	μ_3	μ_4	μ_5	σ^2	p_{11}	p_{12}	p_{13}	p_{21}
Estimate	8.12	3.39	1.19	1.19	-4.42	3.60	0.56	0.28	0.16	0.07
Std error	0.57	0.33	0.68	1.05	0.80	0.29	0.10	0.14	0.13	0.04
	p_{22}	p_{23}	p_{25}	p_{31}	p_{32}	p_{33}	p_{35}	p_{41}	p_{42}	p_{44}
Estimate	0.88	0.04	0.00	0.04	0.04	0.73	0.19	0.49	0.22	0.00
Std error	0.07	0.05	0.09	0.14	0.09	0.12	0.11	0.23	0.26	0.20
	p_{45}	p_{51}	p_{52}	p_{54}	p_{55}	**Likelihood**				
Estimate	0.29	0.07	0.00	0.64	0.29	-509.83				
Std error	0.19	0.08	0.36	0.22	0.27					

The results are given in Table 4 above and are supportive of a stall state using the definition in Sheets and Sockin. In particular, recessions do not directly follow periods of normal growth ($p_{25}=0$), but instead transition through the low-growth state. Also, the transition probability from this low-growth state to recession, p_{35}, is much higher than the probability of returning to higher growth $(p_{31}+p_{32})$.

Interestingly, the state that corresponds to low growth following recessions is a purely transitory state in this calibrated version of the model. Following a recession, the economy typically transitions through a low-growth state ($p_{54} = 0.64$) for one period ($p_{44} = 0$), before either returning to recession ($p_{45} = 0.29$) or moving on to higher growth ($p_{41} + p_{42} = 0.71$). We leave further examination of these transition probabilities to future work.

Conclusions

Low positive GDP growth has been interpreted as evidence that the economy may be "stalling", implying that low growth is a strong predictor of future recessions. We looked for empirical evidence of stalling in US GDP, and found that this is very sensitive to how a stall is defined. If low growth constitutes a stall, as in Nalewaik (2011), then US GDP does not stall. In contrast, if a stall is characterised by a decline in the growth rate of GDP to below some positive threshold, as in Sheets and Sockin (2012), then US GDP does stall.

Sheets and Sockin clearly identify an empirical regularity that is helpful in predicting recessions in-sample, and may also be useful for forecasting future recessions. However, it is not clear that this represents a stall in the aeronautical sense of the word. Too low a flight speed is destabilising, irrespective of what preceded it. Thus, if low growth represents stalling, then low growth following a recession should increase the likelihood of a second ("double dip") recession. Instead, low growth commonly follows recessions, and this is typically followed by higher growth rather than double dips.

More generally, the fact that the economy typically transitions through a low-growth state when both entering and leaving recessions suggests that the economy is highly inertial. Returning to aeronautical analogies, perhaps the slowing economy is like a gliding aircraft. There is insufficient power for the aircraft to overcome the force of gravity, but the wings are experiencing normal lift and flight control is not compromised. There is no fundamental change in underlying economic relationships in the economy as the growth rate falls. Maybe it takes time for a change in pilot inputs, in the form of fiscal policy and monetary policy, to influence the speed of the aircraft, so that the inevitable shocks to the flight path see the aircraft's altitude decrease before rising again, creating the business cycle. Consistent with a highly inertial process, our estimates in Table 4 imply that the economy typically "stalls" for four quarters before entering a recession; in contrast, an aircraft stall occurs at a point in time.

Stepping back, there is a more fundamental problem with using a stall as an analogy for the macroeconomy. As Sheets and Sockin (2012) point out, growth does not fall forever. The economy is self-correcting. Even without any input from outside, wages and prices will adjust and Keynes' (1936) "use, decay and obsolescence" guarantee that demand will eventually rebound so that a recession gives way to economic growth.[12] True, correct inputs by policymakers can smooth the path of the business cycle, and incorrect inputs can make it more turbulent. But ultimately the economy will grow again, regardless of pilot input. In contrast, if an aircraft stalls, there are no self-correcting mechanisms at work. Failure by the pilots to apply the correct inputs will lead to a crash and loss of both the aircraft and its passengers. Perhaps we need a better analogy, based on a cycle that is ultimately self-equilibrating, like the business cycle.

[12] See also Krugman (2012).

Appendix 1: Full Markov switching estimation results

Model 1: Two-state, estimated recession state

	μ_1	μ_2	σ^2	**Likelihood**	p_{11}	p_{22}
Estimate	4.18	–0.92	8.71	–534.90	0.94	0.76
Std error	0.31	0.73	0.46		0.03	0.11

Model 2: Two-state, calibrated recession state

	μ_1	μ_2	σ^2	**Likelihood**	p_{11}	p_{22}
Estimate	4.12	–1.28	8.72	–534.99	0.95	0.77
Std error	0.30	0.75	0.45		0.03	0.11

Model 3: Three-state, estimated recession state

	μ_1	μ_2	μ_3	σ^2	**Likelihood**	p_{11}	p_{22}	p_{33}	p_{21}	p_{32}
Estimate	7.99	2.85	–3.39	4.71	–526.37	0.54	0.84	0.55	0.10	0.35
Std error	0.56	0.26	0.60	0.32		0.12	0.05	0.14	0.04	0.14

Model 4: Three-state, calibrated recession state

	μ_1	μ_2	μ_3	σ^2	**Likelihood**	p_{11}	p_{22}	p_{33}	p_{21}	p_{32}
Estimate	7.90	3.30	–1.28	6.02	–527.31	0.64	0.90	0.77	0.04	0.08
Std error	0.69	0.32	0.50	0.44		0.13	0.05	0.71	0.03	0.08

Model 5: Three-state, estimated recession state, imposing $p_{21} = p_{23}$

	μ_1	μ_2	μ_3	σ^2	**Likelihood**	p_{11}	p_{22}	p_{33}	p_{21}	p_{32}
Estimate	8.02	3.03	–2.80	5.17	–526.74	0.59	0.87	0.61	0.07	0.28
Std error	0.62	0.28	0.60	0.37		0.13	0.05	0.13	0.04	0.13

Model 6: Three-state, calibrated recession state, imposing $p_{21} = p_{23}$

	μ_1	μ_2	μ_3	σ^2	**Likelihood**	p_{11}	p_{22}	p_{33}	p_{21}	p_{32}
Estimate	7.87	3.24	–1.28	5.92	–527.45	0.62	0.90	0.77	0.05	0.09
Std error	0.69	0.32	0.51	0.45		0.13	0.05	0.10	0.04	0.08

Model 7: Three-state, estimated recession state, imposing $p_{21} = 0$

	μ_1	μ_2	μ_3	σ^2	**Likelihood**	p_{11}	p_{22}	p_{33}	p_{32}
Estimate	5.96	3.17	–1.28	7.43	–528.41	0.89	0.94	0.77	0.05
Std error	0.60	0.39	0.65	0.36		0.05	0.04	0.11	0.11

Model 8: Three-state, calibrated recession state, imposing $p_{21} = 0$

	μ_1	μ_2	μ_3	σ^2	**Likelihood**	p_{11}	p_{22}	p_{33}	p_{32}
Estimate	5.96	3.06	–2.12	7.29	–527.86	0.90	0.94	0.71	0.06
Std error	0.56	0.36	0.72	0.34		0.04	0.03	0.12	0.11

Model 9: Four-state, estimated recession state

	μ_1	μ_2	μ_3	μ_4	σ^2	p_{11}	p_{12}	p_{13}	p_{21}	p_{22}	p_{23}	p_{24}
Estimate	8.12	3.39	1.19	–4.42	3.84	0.59	0.20	0.21	0.04	0.91	0.06	0.00
Std error	0.49	0.31	0.63	0.87	0.25	0.11	0.13	0.14	0.04	0.07	0.08	0.10
	p_{31}	p_{32}	p_{33}	p_{34}	p_{41}	p_{42}	p_{43}	p_{44}	**Likelihood**			
Estimate	0.21	0.09	0.49	0.21	0.07	0.00	0.62	0.31	–526.74			
Std error	0.09	0.10	0.15	0.12	0.08	0.29	0.33	0.18				

Appendix 2: Full out-of-sample forecasting mean square error results

Horizons	1	2	3	4	5	6	7	8	9	10
Forecast period: Q2 1981-Q4 2007										
Estimated recession state										
Model 1: Two-state	6.25	6.94	7.15	7.31	7.90	7.72	7.54	7.49	7.11	6.94
Model 3: Three-state	6.11	6.74	7.06	6.88	7.53	7.54	7.29	7.40	7.01	6.95
Model 5: Three-state, imposing $p21 = p23$	6.30	6.89	7.27	7.17	7.76	7.57	7.32	7.33	7.01	6.95
Model 7: Three-state, imposing $p21 = 0$	6.22	6.87	7.05	6.95	7.45	7.53	7.28	7.40	7.07	7.01
Calibrated recession state										
Model 2: Two-state	6.22	6.87	6.99	7.25	7.85	7.68	7.51	7.46	7.05	6.86
Model 4: Three-state	5.91	6.42	6.69	6.88	7.57	7.44	7.37	7.38	7.02	6.88
Model 6: Three-state, imposing $p21 = p23$	5.83	6.56	6.80	6.97	7.65	7.51	7.39	7.38	7.05	6.88
Model 8: Three-state, imposing $p21 = 0$	5.87	6.70	6.91	6.92	7.42	7.27	7.17	7.28	6.93	6.77
Forecast period: Q1 1990-Q4 2007										
Estimated recession state										
Model 1: Two-state	4.86	5.21	5.98	6.59	7.06	7.25	7.26	7.25	7.23	7.30
Model 3: Three-state	4.62	4.96	5.70	6.36	6.93	7.13	7.19	7.20	7.23	7.29
Model 5: Three-state, imposing $p21 = p23$	4.65	4.92	5.77	6.49	7.04	7.28	7.33	7.34	7.35	7.41
Model 7: Three-state, imposing $p21 = 0$	4.77	5.10	5.86	6.43	6.83	6.98	7.11	7.15	7.25	7.32
Calibrated recession state										
Model 2: Two-state	4.89	5.16	5.89	6.53	6.99	7.16	7.14	7.12	7.08	7.13
Model 4: Three-state	4.56	4.75	5.65	6.29	6.88	7.01	7.10	7.08	7.09	7.15
Model 6: Three-state, imposing $p21 = p23$	4.58	4.83	5.68	6.39	6.97	7.20	7.24	7.24	7.24	7.27
Model 8: Three-state, imposing $p21 = 0$	4.58	4.96	5.79	6.31	6.60	6.77	6.87	7.02	7.04	7.05
Forecast period: Q1 1990-Q4 2007										
Estimated recession state										
Model 1: Two-state	5.37	4.94	6.41	9.27	10.60	11.13	10.61	10.59	10.56	10.63
Model 3: Three-state	4.62	4.10	5.70	8.82	10.36	10.93	10.45	10.47	10.53	10.59
Model 5: Three-state, imposing $p21 = p23$	4.83	4.37	5.99	9.12	10.62	11.24	10.75	10.75	10.79	10.85
Model 7: Three-state, imposing $p21 = 0$	4.33	4.15	5.63	8.79	10.05	10.65	10.21	10.36	10.52	10.61
Calibrated recession state										
Model 2: Two-state	5.44	4.84	6.28	9.14	10.40	10.85	10.29	10.26	10.21	10.25
Model 4: Three-state	4.59	4.02	5.49	8.57	10.09	10.58	10.10	10.10	10.18	10.26
Model 6: Three-state, imposing $p21 = p23$	4.81	4.29	5.91	8.97	10.43	10.98	10.48	10.48	10.51	10.57
Model 8: Three-state, imposing $p21 = 0$	4.67	3.97	5.38	8.08	9.23	9.67	9.31	9.55	9.65	9.75

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