Revenue Cycles and the Distribution of Shortfalls in U.S. States: Implications for an 'Optimal' Rainy Day Fund*

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January 2006

Abstract

Slowdowns in economic activity often leave state policymakers facing severe budget shortfalls and the prospects of reducing services. In this paper we make use of a Markov switching regression to model, in a probabilistic sense, the expansion-contraction behavior of each state's revenue growth. This allows us to not only construct probability distributions of the revenue shortfalls states are likely to confront during recessions, but also to construct savings rate rules based on the uncertainty in both expansions and contractions. Our results have important implications for policymakers who wish to smooth cyclical fluctuations through the use of a rainy day fund.

JEL classification codes: H6, H7, G1
Keywords: fiscal stress, revenue shortfalls, business cycles, regime-switching

* The authors would like to thank Michael Owyang, David DeJong, Michael Dueker, Dennis Coates, Jon Rork, and seminar participants at Vassar College, National Tax Association, and Southern Economic Association for many valuable comments and suggestions. Any remaining errors are the sole responsibility of the authors.

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1. Introduction

Slowdowns in economic activity often leave state policymakers facing severe budget shortfalls and the prospects of reducing vital services. Due to the most recent downturn for example, the National Association of State Budget Officers (NASBO) reported that compared to FY2002, twenty-one states had negative general fund spending in FY2003 and forty states reduced budgeting spending by nearly $12 billion during the year. Given the long expansion of the 1990s, the beginning of the 21st century was an unwelcome period of adjustment for many policymakers.

Despite the importance and attention placed on state fiscal problems during slowdowns, only a handful of studies have attempted to quantify the "fiscal stress" that states experience due to recessions. This is important because, unlike the federal government, the options available to policymakers at the subnational level for mitigating recessions are limited by institutional constraints such as balanced budget rules, borrowing restrictions, and tax limitation laws (Poterba 1994). As a result, the number of states utilizing a rainy day fund to help accumulate reserves and reduce the cyclical fluctuations in the budget has grown from fewer than ten states in 1980 to forty-six states by the start of the 2001 recession.

In this paper we make use of a two-regime Markov switching regression, popularized by Hamilton (1989), to model the business cycle behavior of each state's revenue growth. This model has not been previously applied in the arena of state government finance and it allows us to describe, in a probabilistic sense, the expansion-contraction behavior of state revenue and extend the literature measuring state fiscal stress in several key areas. First, while previous authors have modeled the probability distribution of downturns states are likely to experience in one fiscal year, we allow the duration of downturns to persist for an arbitrary number of periods to explore the expected impact of multi-year recessions on state revenue. Second, the regime-switching model allows expansions and contractions to be described by (potentially) distinct distributions, as opposed to a single distribution. Finally, and most importantly, if policymakers wish to save during periods of growth to hedge against downturns, then knowledge of an expected shortfall is of limited value because the duration of expansions are also unknown *a priori*. In other words, if two states are expected to experience identical fiscal stress during a normal downturn (say 10 percent of the budget), then the amount policymakers should save during each expansion year to guard against the downturns will be different depending on the expansions that are likely to prevail in their state. Thus, based on the probability distribution of expansions *and* contractions, we calculate the fraction of revenue that policymakers should save during each expansion year to hedge all of the possible expansion-contraction combinations that may occur in their state. This issue has not be addressed in a meaningful way in the literature and if policymakers wish to use a rainy day fund as a means of insuring against downturns, then knowledge of a savings rate rule is arguably of more value than knowledge of an expected shortfall.

In the following sections of the paper we review previous research, outline our empirical methodology and findings, and offer concluding remarks.

2. Previous Research and the Measurement of State Fiscal Stress

2.1 Literature review

Previous studies have addressed the issue of measuring fiscal stress in the context of an "optimal" rainy day fund because if policymakers wish to guard against recessions via a savings instrument, then knowledge of the fiscal stress they are expected to encounter is essential.[1]

The most widely-adopted methodology for quantifying fiscal stress in the literature is to provide a single point-estimate that is based on the cumulative deviation from a linear trend. For example, Sobel and Holcombe (1996a) use the sum of the cumulative shortfalls in expenditures and revenues from their respective linear trends over the period from 1989 to 1992 to determine how large each state's rainy day fund should have been to maintain trend expenditures and revenues during the 1990-91 recession. After adjusting the data for discretionary changes, Sobel and Holcombe find that state fiscal stress *averaged* 30 percent of FY1988 expenditures, but ranged from a low of 5 percent in Wisconsin to a high of 88 percent in Connecticut. Similarly, Pollock and Suyderhoud (1986) and Navin and Navin (1997) investigate the behavior of an individual state (Indiana and Ohio respectively) over a much longer period of time and suggest that savings equal to 11 and 13 percent of the budget respectively would be sufficient to offset a normal downturn. Pollock and Suyderhoud computed fiscal stress as the sum of the average cumulative shortfalls in expenditures and revenues from trend, while Navin and Navin used the average cumulative deviation in revenue from trend.[2]

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[1] The use of the term "optimal" simply refers to the notion that if a state normally experiences fiscal stress from recessions equal to 10 percent of revenue, then savings equal to 10 percent of revenue would be sufficient to offset the slowdown. It is not meant to imply what may be optimal from the perspective of policymakers, citizens, or savings instruments. For recent work on issues relating to the political and institutional constraints facing state policymakers, as well as the effectiveness of rainy day funds, see Wagner and Elder (2005), Wagner (2004), Cornia and Nelson (2003), and Mattoon (2003).

[2] In addition to differences in examining revenues or the sum of revenues and expenditures, the data employed to measure fiscal stress have varied as well. For instance, Sobel and Holcombe use total revenue and total expenditure data, Pollock and Suyderhoud use general fund revenues and expenditures, and Navin and Navin use own-source general fund revenue data. A potential problem with using the sum of the deviation in revenues and expenditures from trend is that this approach does not take into account any causality that may exist. For example, expenditures could be below trend *because* revenues are below trend.

A limitation of the aforementioned studies is that they rely entirely on *ex post* information without incorporating the fact that business cycle phases are unknown *a priori.* A more realistic and useful approach from the perspective of policymakers would be to model the distribution of fiscal stress states are likely to encounter during downturns.

Cornia and Nelson (2003) were the first to construct a probabilistic model of fiscal stress that is based on the concept of value-at-risk (VaR), which is a common technique for modeling portfolio risk in the finance literature. In short, the essence of VaR analysis is a confidence interval approach based on a distribution of possible outcomes. Thus, given a mean, standard deviation, and a distribution regarding the behavior the data/portfolio (typically assumed to be normal), an empirical distribution may then be constructed from all of the possible outcomes and the associated probability that each outcome will occur. For a given time horizon and level of confidence such as *x* percent, the value-at-risk is the outcome above which *x* percent of the possible outcomes lie. Cornia and Nelson examine Utah's budget surplus/deficit for FY2003 using a time horizon of one year and estimate that there is a 95 percent chance the deficit will be less than or equal to $135 million. This is equivalent to stating that there is less than a 5 percent chance Utah will experience a deficit in FY2003 in excess of $135 million.

Although Cornia and Nelson do not explore longer time horizons, the VaR methodology may be extended to multiple periods. This is important in the context of state-level recessions because Owyang *et al*. (2005) find that the typical state's recession lasts for nearly 20 months, so limiting the time horizon to one year could underestimate the average state's expected fiscal stress by 60 to 70 percent. A key aspect of extending VaR analysis to multiple periods rests with the assumption of how the outcomes are being drawn. If the periods are assumed to be independently, identically, and normally distributed (n.i.i.d.), then the mean and standard deviation of the *t*-period distribution is given by $t\mu$ and $\sigma\sqrt{t}$, where μ and σ denote the mean and standard deviation from the single-period distribution. In contrast, if the distribution of outcomes is not assumed to be n.i.i.d., but instead there are multiple, distinct distributions describing the outcomes, then it becomes necessary to also know the probability that draws are from a particular distribution prior to performing VaR analysis. Billio and Pelizzon (2000) apply such a multi-period VaR to stock portfolios and estimate the probabilities that outcomes are from a given distribution by use of a Markov switching regression.

If a multi-period framework is employed and the possible outcomes are permitted to be drawn from multiple (possibly distinct) distributions instead of a single distribution, then our approach would be similar, but not identical to, a standard multi-period VaR analysis. They are similar to the extent that confidence intervals are formed based on a distribution of possible outcomes, but the methodologies differ in the treatment of the time horizon. VaR analysis, as it is applied in the finance literature, examines a fixed number of time periods. Thus, such an approach is useful to address the question "What is the maximum fiscal stress a state can expect to experience over the next *t* years with a given level of certainty?". However, because the duration of state fiscal cycles are unknown in advance, the regime-switching approach allows us to model fiscal stress based on each state's fiscal cycle in place of a fixed number of time periods. Thus, we address the question "What is the maximum fiscal stress a state can expect to encounter over the next fiscal cycle (the duration of which is unknown) with a given level of certainty?".

The findings of Owyang *et al*. (2005), along with our empirical results presented later in the paper, provide evidence in favor of a multi-period approach. Moreover, permitting the outcomes to be drawn from multiple distributions allows for potential asymmetry in state business cycles because expansions and contractions are drawn from separate (and possibly different) probability distributions. Diebold and Rudebusch (1996) argue that the treatment of expansions and contractions as different probabilistic events has been the dominant view of business cycle research since the 1940s.

2.2 Measuring state fiscal stress

The measurement of state fiscal stress, at least conceptually, merely involves quantifying how downturns force revenues and expenditures to deviate from the "norm." Since tax bases are procyclical and tend to be more volatile than state economies, holding tax rates constant over the business cycle and assessing the decline in revenue would capture the revenue side. Given Dye and McGuire's (1999) finding that several components of spending, such as public welfare and AFDC, tend to increase during downturns, expenditure-side fiscal stress could be evaluated by allowing social assistance spending to increase holding non-welfare spending constant. A natural measure of state fiscal stress would therefore be the state's cyclical surplus/deficit because it would capture the response of both revenues and expenditures to downturns.

From a practical perspective, it may be possible to construct a cyclical deficit/surplus series for each state that is equal to the difference between the cyclical components of revenue and spending, holding constant tax rates and non-welfare spending. The behavior of these cyclical deficits could then be modeled to determine both the magnitude of a deficit each state is likely to face during a downturn, as well as how states may accumulate savings during the cyclical surplus to hedge against the deficits.

A potential problem arises with using the cyclical deficit because studies as Knight *et al*. (2003), Baker *et al*. (2002), and Kusko and Rubin (1993) find evidence that state budgets are structurally imbalanced.[3] If a structural deficit is present for instance, then how meaningful and intuitive is a model of the business cycle behavior of a state's cyclical deficit? Suppose, using the cyclical deficit as the measure of fiscal stress, it is estimated that a state would require savings equal to 10 percent of revenue (to be accumulated during an expansionary phase when the cyclical surplus is positive) in order to weather 75 percent of the possible cyclical deficits that may arise during downturns. This level of savings would be sufficient to close the gap between *cyclical* revenue and *cyclical* spending in three out of every four recessions, but it would be *insufficient* to close the gap between *actua*l revenue and *actual* spending in three out of four recessions due to the structural gap. In addition, if a structural gap is present, then a state's actual budget position could be in a deficit at a time when the cyclical position is one of surplus.

Given the structural deficit issue, we assess fiscal stress by modeling the business cycle behavior of revenue growth in place of a deficit measure. The advantage of examining revenue growth is that our results are very intuitive and readily comparable across states. The obvious disadvantage is that our estimates will not include fiscal stress generated from the expenditure side of the budget.[4] Hence, our results provide a conservative look at state fiscal cycles and

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[3] Knight *et al*. (2003) and Kusko and Rubin (1993) reach their conclusion using a high-employment budget surplus/deficit measure for the aggregate state and local sector. Baker *et al*. (2002) examine the present value of projected expenditures, revenues, and net debt of individual states in FY1999 and find that well over half of the states have structural deficits. The high-employment budget approach uses data from the National Income and Product Accounts and Kusko and Rubin (1993) discuss the difficulties in applying this approach to individual states due to data limitations.

[4] In examining the high-employment deficit for the aggregate state and local sector, Kusko and Rubin (1993) note that "the bulk of the cyclical influence on state and local budgets is on the receipts side of the ledger" (p. 413). Moreover, Sorensen and Yosha (2001), who examine how individual state total revenues and expenditures react to current and lagged output changes, also find that revenues respond much more strongly than expenditures to the business cycle. This suggests that, while social assistance spending is countercyclical, the majority of state fiscal stress may in fact manifest itself through the revenue side of the budget. In addition, the Personal Responsibility and Work Opportunity Reconciliation Act of 1996 altered the social assistance funding mechanism between the states and federal government. States now receive an annual block grant, as opposed to matching grants, and are able to retain surplus funds for use in future years, which could improve their ability to absorb increased caseloads during downturns. For a recent overview of the sensitivity of state social assistance spending to the business cycle see McGuire and Merriman (2005).

should be viewed as the *minimum fiscal stress* that states are likely to experience during a downturn.

3. Empirical Methodology and Data Description

3.1 Regime-switching model

The motivation behind regime-switching models is that many time series appear to be generated from multiple, distinct data generating processes. As Hamilton (1994) notes, structural breaks or regime changes in a data series may be triggered by a variety of factors including economic downturns, policy changes, and financial crises. If regime changes are assumed to be perfectly predictable events and known *a priori*, then an empirical model incorporating the parameter instability that such regime switching implies can easily be constructed with dummy variables. A more realistic assumption is that the timing of the regime changes are unknown.

Econometric models featuring parameter instability with unknown turning points (or regime changes) were first analyzed by Quandt (1958). Goldfeld and Quandt (1973) provided a valuable extension to Quandt's model by permitting multiple (unknown) regime switches that were governed by a Markov process so that the timing of the regime switches was dependent on which regime was in effect.

The extensive use of regime-switching models over the last decade, particularly in the macroeconomic and financial literature, is largely due to Hamilton's (1989) extension of the Goldfeld and Quandt model to include serially dependent data. Hamilton applied a two-regime autoregression to the quarterly growth rate in real U.S. Gross National Product in which the regimes exogenously switched according to an unobserved Markov process. The best fit occurred when the mean growth rate in one regime was 1.2 percent (an expansion regime) and the mean growth rate in the second regime was -0.4 percent (a contraction regime). Each regime also exhibited considerable persistence, with the probability of remaining in an expansion (contraction) in period *t* given that the economy was expanding (contracting) in period *t-1* estimated to be 0.90 (0.75). Perhaps the most notable feature of Hamilton's model was that the estimated timing of regime switches closely matched the official NBER business cycle turning points.

Despite the widespread application of regime-switching models to aggregate data, only Owyang *et al*. (2005) have applied the methodology to U.S. states. Using Crone's (2002) state-level monthly coincident index, Owyang *et al*. estimate a two-regime Markov switching model with no autoregressive dynamics for each state to identify business cycle turning points and explore the extent to which state-level business cycles mimic the aggregate economy. They find that while state cycles generally follow the aggregate economy, individual states may shift into an expansion or contraction before that national economy shifts, continue in an expansion while the national economy contracts, and experience a downturn that is not associated with an aggregate downturn.

Our empirical specification follows Owyang *et al.* (2005).[5] If a state's revenue growth at time *t* is denoted as $\dot{R}_t$, then the two-regime Markov switching model with no autoregressive dynamics may be written as:

$$\dot{R}_t = g_{S_t} + \varepsilon_t,$$

$$g_{S_t} = \begin{cases} g_H & \text{if } S_t = 0 \\ g_L & \text{if } S_t = 1 \end{cases}, \tag{1}$$

[5] We explored the use of autoregressive terms in each state but did not find evidence to support their inclusion. This is not surprising given that we apply the model to annual data.

$$\varepsilon_t \sim N(0, \sigma_\varepsilon^2),$$

where g denotes the mean growth rate of $\dot{R}_t$ and ε_t is the zero-mean innovation at time t assumed to be normally distributed with variance σ_ε^2. The mean growth rate in (1) may switch between two regimes and the switches are assumed to be exogenous and governed by an unobserved regime variable, $S_t = \{0,1\}$. Thus when $S_t = 0$, which we refer to as the high-growth regime, the behavior of $\dot{R}_t$ follows a stationary AR(0) process with a mean growth rate of g_H. When S_t switches from 0 to 1, which we call the low-growth regime, the mean growth rate switches from g_H to g_L. Given that there are no autoregressive dynamics, the model assumes that $\dot{R}_t$ evolves as a mixture of two normal distributions that have the same variance but potentially different means.[6]

Although S_t is assumed to be unobserved, we may infer which regime is in effect by placing restrictions on the behavior of S_t. We do this using the standard assumption that S_t evolves according to a first-order two-state Markov chain with the following transition matrix:

$$\boldsymbol{P} = \begin{bmatrix} P(S_t = 0 \mid S_{t-1} = 0) & P(S_t = 1 \mid S_{t-1} = 0) \\ P(S_t = 0 \mid S_{t-1} = 1) & P(S_t = 1 \mid S_{t-1} = 1) \end{bmatrix} = \begin{bmatrix} P_{HH} & 1 - P_{HH} \\ 1 - P_{LL} & P_{LL} \end{bmatrix}, \quad (2)$$

where P_{ij} is the transition probability of $S_t = i$ given that $S_{t-1} = j$. Hence, P_{HH} is the probability that revenue growth is in the high-growth regime in period t conditional on having been in the high-growth regime in period *t-1*.

Following Owyang *et al*. (2005), we estimate (1) and (2) using the Bayesian Gibbs-sampling approach for Markov switching models developed by Kim and Nelson (1998). Since a

[6] Although we expect $g_H > 0$ and $g_L < 0$, Owyang *et al.* (2005) find that the low-regime growth rates in Arizona, Delaware, New Mexico, and New York are positive and close to zero. This suggests, on average, that these states' economies (as measured by Crone's (2002) monthly index) do not contract during downturns but rather grow at a very slow rate.

step-by-step description of the sampling procedure is provided in Kim and Nelson (1999), we will only briefly review it here.[7] Kim and Nelson's Bayesian approach treats the model's parameters (g_H, g_L, P_{HH}, P_{LL}, σ_ε^2) and unobserved regime variable (S_t) as unknown random variables that can be evaluated from sampling from the appropriate conditional posterior distributions. The draws from the conditional posterior distributions form an irreducible Markov chain that converges to the joint posterior distribution of the parameters conditional on the data. The joint posterior distributions were simulated using 10,000 replications with an additional 2,000 burn-in replications.

The appropriate prior distributions for the Markov regime-switching model were derived by Albert and Chib (1993). Given that this is the first study to explore the business cycle phases of state revenue growth, we use relatively diffuse priors based on Owyang *et al.*'s (2005) estimates so that the joint posterior distribution depends much more heavily on the observed data than on any prior beliefs regarding the parameter values.[8] Thus, the transition probabilities, P_{HH} and P_{LL}, have prior Beta distributions of $\beta(6, 2)$ and $\beta(2,3)$ respectively, implying means of .75 and .40 with standard deviations of .38 and .44. The prior distributions for g_H and g_L are assumed to be normal with means of 4.8 and –3 respectively, which are Owyang *et al.*'s mean (annualized) growth rate estimates. We introduce our uncertainty about the regime growth rates by allowing the variance of the prior distributions of g_H and g_L to be equal to 5 and the covariance between g_H and g_L to be equal to zero. Finally, the prior distribution for σ_ε^2 follows

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[7] We acknowledge use of the computer routines described in Kim and Nelson (1999).

[8] Although Owyang *et al.*'s (2005) study provides an estimate of each state's expansion and contraction growth rates and the associated transition probabilities, we opted for diffuse priors for two primary reasons. First, Owyang *et al.* examine a much shorter time period with higher frequency data. Second, it is unclear how closely a state's annual revenue growth may be linked to the monthly coincident index examined by Owyang *et al.*

an improper inverted-Gamma distribution with a mean of 20 and a variance of 10. Appendix B of the paper illustrates the diffuse prior distributions for P_{HH}, P_{LL}, g_H, and g_L.

3.2 Data description

The empirical model is applied to the growth rate in each state's real per capita total revenue over the period from 1960 to 2003.[9] Because these revenue data include discretionary changes and therefore may not reflect how revenue would change over the business cycle holding tax rates constant, we construct a revenue series for each state to minimize the effects of policy changes. Our "policy-reduced" revenue series is obtained by predicting the growth in revenue as a function of personal income growth, holding constant the long-run relationship between revenue and personal income. This is achieved by estimating an error correction model for each state given by:

$$\dot{R}_t = \alpha + \beta \dot{Y}_{t-1} + \delta D_t + \lambda \hat{\varepsilon}_{t-1} + \upsilon_t , \qquad (3)$$

where $\dot{R}_t$ and $\dot{Y}_{t-1}$ denote the growth rates (logged first difference) in real per capita total revenue and real per capita personal income respectively, υ_t is the zero-mean Gaussian innovation, and $\hat{\varepsilon}_{t-1}$ is the one-period lag of the estimated residual from the cointegrating

[9] The beginning data of our sample was limited to 1960 because total revenue data is not available for every state before 1960. Total revenue data were obtained from various issues of *State Government Finances* published by the U.S. Census Bureau. State population and personal income data are from the Bureau of Economic Analysis and all real variables were deflated using the seasonally adjusted Consumer Price Index for all urban consumers (1982-1984=100) obtained from the Bureau of Labor Statistics. In addition, Wyoming's total revenue in 2000 was an extreme outlier that had a substantial effect on the state's estimates. Wyoming's total revenue was $5,740 (millions of nominal dollars) in 2000, compared to $3,092 in 1999 and $2,880 in 2001, because of insurance trust revenue equal to $3,338. The average state's insurance trust revenue in 2000, excluding Wyoming, was equal to 25 percent of general fund revenue (compared to 142 percent in Wyoming). We adjusted the 2000 observation in Wyoming by assuming the state received insurance trust revenue equal to 25 percent of general fund revenue. This would make the state's insurance trust revenue equal $589 (instead of $3,338) and total revenue equal to $2,991 (instead of $5,740).

regression in levels given by $\ln(R_t) = \varphi + \pi \ln(Y_{t-1}) + \varepsilon_t$.[10] Finally, D_t is an indicator variable that equals unity if $\hat{\varepsilon}_t < 0$ and equals zero otherwise. The inclusion of D_t allows the intercept to vary depending on whether revenue growth at time *t* is above or below its long-run equilibrium. Personal income in equation (3) is lagged one period because these data are calculated using calendar years and revenue data are in fiscal years.

While there is no perfect way to remove policy changes from the data, the methodology we propose seems reasonable.[11] For example, the mean growth rate in actual real per capita total revenue for all states was 3.07 percent in our sample period, with a mean positive growth rate of 6.06 percent and a mean negative growth rate of -4.54 percent (computed using only the positive and negative revenue growth observations respectively). In the policy-reduced series, the overall mean growth rate remains 3.07 percent, but the mean positive growth rate drops to 5.02 percent and the mean negative growth rate increases to -3.08. The reason these changes occur is because the policy-reduced series has more persistence in both the positive and negative growth observations. In short, while 72 percent of the total number of positive growth observations and 32 percent of the total number of negative growth observations occurred in back-to-back years in

[10] As a necessary condition for cointegration, we examined the stationarity of the log of total revenue and personal income (both in real per capita terms) using the Augment Dickey-Fuller test and were unable to reject the null hypothesis of a unit root in each state. The null hypothesis that the variables are not cointegrated was tested, and rejected in each state, using Phillips and Ouliaris's (1990) residual-based P_Z and P_U that included a constant term in the cointegrating regression. We used both the P_Z and P_U test statistics as a robustness check because the P_U test, but not the P_Z test, depends on the normalization of the cointegrating vector. Finally, to avoid the problems of serial correlation, endogeneity, and non-normal residuals that may arise if variables are cointegrated, the estimated residual in (3) was obtained from estimating the cointegrating regression for each state using Phillips and Hansen's (1990) fully-modified OLS estimator. The results of the unit root tests, cointegration tests, and cointegrating regressions are not reported in the paper but are available from the authors upon request.

[11] Given that a number of papers, such as Sobel and Holcombe (1996b) and Dye and McGuire (1991), estimate elasticities of various tax bases, a natural choice may be to construct a revenue series from these elasticities because they attempt to hold tax rates constant. There are several potential concerns with such an approach. First, states receive revenue from a variety of sources so an accurate "policy-free" revenue series would require an elasticity for a sizable number of revenue sources. Failing to do so may result in the omission of revenue sources that could be more volatile than the state's economy over the business cycle. Also, examining only the cyclical behavior of tax bases may understate the volatility in personal and corporate income tax revenue because of the progressive rate structures that exist in many states.

the actual revenue data, these figures increased to 79 percent and 35 percent respectively in the policy-reduced series. This additional persistence, especially during downturns, is consistent with removing discretionary changes because policymakers tend to increase taxes during recessions. A state-by-state comparison of the actual and policy-reduced revenue growth rates are provided in Appendix Table A. All of the estimates and discussion of revenue from this point forward in the paper refer to the policy-reduced revenue series.

4. Business Cycle Phases of State Revenue Growth

Parameter estimates from each state's two-regime Markov switching model of (policy-reduced) revenue growth are presented in Table 1. The point estimates we present are the means of the posterior distributions. The expected duration of each regime, as well as a concordance measure (discussed in more detail below), are also presented.

[Table 1 here]

Consistent with Owyang *et al*. (2005), our estimates indicate that there is considerable asymmetry across states concerning growth rates during expansions and contractions. During expansions for instance, the average growth rate in revenue ($\hat{g}_H$) across all states is 4.05 percent, with Alaska experiencing the highest mean expansion growth rate (7.24 percent) and Nevada experiencing the lowest expansion growth rate (2.55 percent). Six states have average expansion growth rates that exceed 4.5 percent, while eight states have expansion growth rates that average less than 3.5 percent. During recessions, the estimated mean growth rate in revenue ($\hat{g}_L$) averages –3.13 percent across all states, with Alaska having the lowest mean recession growth rate of –9.45. Eighteen states have an average recession growth that is greater (more negative) than –3 percent, while eight states have recession growth rates that average less than -2 percent.

The transition probabilities ($\hat{P}_{HH}$ and $\hat{P}_{LL}$) provide further evidence of the asymmetry across states. For instance, given that a state's revenue growth was in an expansion in period *t-1*, there is (on average) a 0.76 probability of revenue growth being positive in period *t*. This probability varies from a high of .81 in North Carolina to a low of 0.69 in Wisconsin. With regard to downturns, the estimates indicate that being in a recession (negative revenue growth) in period *t-1* is associated with (again, on average) a 0.41 probability of being in a recession in period *t*. These probabilities also differ noticeably, ranging from a low of 0.35 in Wisconsin and Minnesota to a high of 0.60 in Alaska.

The columns denoted $E[t_H]$, $E[t_H]$, and $E[t_H] + E[t_H]$, which are computed from the transition probabilities, refer to the expected duration of an expansion, contraction, and revenue cycle respectively.[12] These estimates indicate that a typical state experiences approximately 4.25 years of revenue growth expansion, followed by 1.7 years of revenue growth contraction, resulting in an average revenue cycle of just over 6 years. This average revenue cycle coincides closely with Owyang *et al.*'s (2005) cycle lengths, but there is considerable variation as our estimated revenue cycles range in length from just over 7 years in North Carolina to under 5 years in Wisconsin. Despite the variation that exists across states, the estimates indicate that the baseline regime for all states is one of revenue growth.

Overall, the regime-switching models seem to characterize the cyclical behavior of state revenue growth very well. The estimated mean expansion and contraction growth rates (averaged across all states) of 4.05 and –3.13 are credible in comparison to the positive- and negative-growth means (averaged across all states) of 5.02 and –3.08 in the policy-reduced

[12] Given the probability of being in a high-growth (P_{HH}) or low-growth regime (P_{LL}) in period *t* conditional on being in the same regime in period *t-1*, Hamilton (1994) shows that the expected duration of a given regime may be computed as $E[\, t_j \,] = (1 - P_{jj})^{-1}$ for $j = H,L$.

revenue data. In addition, the concordance measure presented in the final column of Table 1, which is the percentage of the *T* observations for each state in which the Markov switching model predicts a high-growth (low-growth) regime at time *t* and the state's revenue growth is also positive (negative) at time *t*, shows a mean concordance of 0.84.[13] The concordance measure is *not* a measure-of-fit for the regime-switching model because, by construction, the concordance assumes the regimes are in fact observed, which violates a basic assumption of the model. However, given that state-level business cycles are not formally dated, we report the concordances because they do provide at least some evidence that the expansions and contractions identified by the Markov switching model are very closely related to the positive- and negative-growth observations in the data.

Although a detailed examination of the factors contributing to the asymmetries across states could be insightful, it is beyond the scope of this paper. There are several potential explanations for the variation across states that are worth briefly mentioning. First, structural differences in state economies may play a role. Owyang *et al*. (2005) find that expansion growth rates depend largely on a state's demographic and education composition, while recession growth rates depend on the state's industry mix. *Ceteris paribus*, states with more employment in manufacturing, construction, and mining face significantly more negative recession growth rates. Second, a state's tax system may contribute to the differences. States that rely more heavily on procyclical tax bases, such as a retail sales tax that exempts food or corporate income, may experience more volatile growth rates. In addition, Dye and McGuire's (1998) finding that the

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[13] The concordance is given by C = $\frac{1}{T}\sum_{t=1}^{T}[S_{Pt}\,S_{Ot}+(1-S_{Pt})(1-S_{Ot})]$, where *T* denotes the sample size and S_{Pt} and S_{Ot} denote the predicted and "observed" regime phase at time *t*. If the probability of a recession from the regime-switching model at time *t* is estimated to be greater than or equal to .5, then $S_{Pt} = 1$. Otherwise, $S_{Pt} = 0$. Similarly, if the growth rate in a state's policy-reduced revenue series is negative at time *t*, then $S_{Ot} = 1$. Otherwise, $S_{Ot} = 0$. This concordance measure was employed by Owyang *et al*. (2005) to examine the degree to which state-level business cycles coincided with the U.S. economy.

cyclical variability of personal income tax revenue depends on the degree of progressivity suggests that differences in rate structures could also contribute to the disparities across states.[14]

5. Shortfalls, Savings Rules, and Implications for an "Optimal" Rainy Day Fund

5.1 Probability distributions of state revenue shortfalls

The estimated parameters of the regime-switching regressions provide measures of the amplitude and duration of the regimes in a revenue cycle. In this section of the paper we demonstrate how the parameter estimates may be used to construct probability distributions of state revenue shortfalls.

Hamilton (1994) shows that since P_{LL} is the (estimated) probability of being in a low-growth regime in period *t* given that a low-growth regime was in effect in period *t-1*, the probability that a contraction will persist exactly t_L periods may be expressed as $P_L(t_L) = P_{LL}^{t_L - 1} - P_{LL}^{t_L}$. Thus, if one computes each state's shortfall for a contraction regime that persists for $t_L = 1, 2, \ldots, \infty$ periods, and the probability that a shortfall lasting exactly that length will occur, then the values may be used to form a cumulative probability distribution. An *x* percent revenue shortfall can then be easily determined as the shortfall size such that *x* percent of the possible shortfalls are less than this amount.

Since the regime-switching regressions provide an estimate of the mean expansion and contraction growth rates, we may measure the amplitude of a shortfall as either: (i) the difference from zero or (ii) the difference between the average expansion and average contraction. Measuring a shortfall as the difference from zero is useful to determine a rainy day fund size that is adequate to maintain a constant level of revenue throughout a recession with a given level of

[14] For a recent overview of the cyclical variability of state tax revenue and tax bases see Dye (2004).

certainty. If a shortfall is measured as the difference between the average expansion and average contraction, then the shortfall will yield the rainy day fund size that is sufficient to maintain the average expansion growth rate in revenue (which is the baseline regime) during a recession with a given level of certainty. We first examine the distribution of shortfalls by measuring the shortfall as the difference from zero before turning our attention to measuring shortfalls as the difference between the average expansion and contraction.

If a state experiences a high-growth regime that exists for t_H periods, then the level of revenue will be equal to $R_0(1+g_H)^{t_H}$, where R_0 is the initial level of revenue and g_H is the average growth rate (per period) in revenue. Assuming a low-growth regime begins and revenue grows (on average) at the rate of g_L, total revenue in the first low-growth period will be equal to $R_0(1+g_H)^{t_H}(1+g_L)$ and the revenue shortfall in the first low-growth period would be given by $R_0(1+g_H)^{t_H}\left[1-(1+g_L)\right]$. Thus, the shortfall in the first low-growth period relative to revenue in the last high-growth period, which effectively measures the shortfall as a fraction of revenue, would simply be $1-(1+g_L)$. For a recession that lasts t_L periods (following t_H periods of high-growth), the cumulative shortfall (as a share of revenue) may then be expressed as:

$$\varsigma(t_L) = t_L - \sum_{i=1}^{t_L}(1+g_L)^i \,. \tag{4}$$

If the amplitude of a shortfall is measured as the difference between the average expansion and contraction, then the derivation of the cumulative shortfall is slightly different. Assume that a state experiences a high-growth regime that lasts for t_H periods and a low-growth regime begins. If the low-growth regime persists only one period, the revenue shortfall is $R_0\left[(1+g_H)^{t_H+1}-(1+g_H)^{t_H}(1+g_L)\right]$, which is the difference between what revenue would have been if the average expansion revenue growth had continued, $R_0(1+g_H)^{t_H+1}$, and revenue in the first low-growth period, $R_0(1+g_H)^{t_H}(1+g_L)$. If the low-growth regime were to last for two periods, then in the second period, the shortfall in just this period is $R_0\left[(1+g_H)^{t_H+2}-(1+g_H)^{t_H}(1+g_L)^2\right]$ and the cumulative shortfall is $R_0(1+g_H)^{t_H}\left[\sum_{i=1}^{2}(1+g_H)^i-\sum_{i=1}^{2}(1+g_L)^i\right]$. Thus, for a low-growth regime lasting exactly t_L periods, the cumulative revenue shortfall relative to the average expansion regime (expressed as a share of revenue) is:

$$\varsigma_2(t_L)=\sum_{i=1}^{t_L}(1+g_H)^i-\sum_{i=1}^{t_L}(1+g_L)^i\ . \qquad (5)$$

To construct each state's cumulative density function of shortfalls (hereafter CDF), we compute the shortfalls given by equations (4) and (5) assuming a downturn persists for $t_L = 1, 2, ..., 25$ periods (in increments of .1) and calculate the corresponding probability that a contraction lasting exactly t_L periods occurs.[15] We refer to the shortfalls measured as the difference from zero as a "constant-revenue shortfall" and the shortfalls measured as the difference between the average expansion and contraction as a "trend-revenue shortfall." Figure 1 illustrates sample CDFs for a constant-revenue and trend-revenue shortfall using the median parameter estimates in Table 2.

[Figure 1 here]

The 75 percent shortfall values are highlighted in Figure 1. These values indicate that given all of the possible constant-revenue and trend-revenue shortfalls that may occur, there is

[15] In other words, we calculate 250 different shortfalls for each state, using both equations (4) and (5), that vary in length from 0.1 to 25 years in increments of 0.1. Although we could allow the maximum contraction regime to persist for more than 25 years, the likelihood of a recession lasting that long is effectively zero. Alaska has the largest estimated P_{LL} of any state at .60, and the probability that a recession would last 20 years in Hawaii is equal to 0.0000002. In addition, equations (4) and (5) assume that time is an integer value. For incremental values of time, we simply derived an equivalent functional form for (4) and (5) that could incorporate non-integer values.

0.75 probability that a constant-revenue shortfall will be 5.17 percent of revenue (or less) and 0.75 probability that a trend-revenue shortfall will be 12.97 percent of revenue (or less). The two CDFs for each state will vary because the constant-revenue shortfall depends on g_L and P_{LL}, while the trend-revenue shortfall depends on g_L, P_{LL}, and g_H. In Table 2 below we report several constant- and trend-revenue shortfall values for each state.[16]

[Table 2 here]

Table 2 contains two major columns, each with three sub-columns. The major columns entitled "*Constant-Revenue Shortfall*" and "*Trend-Revenue Shortfall*" denote how the amplitude of the shortfall was measured. The sub-columns labeled "*Expected*", "*75%*", and "*90%*" show the expected, 75 percent, and 90 percent shortfall values respectively for each method of measuring the shortfall amplitude.[17]

With regard to the constant-revenue shortfalls for instance, the mean expected shortfall across all states is 6.52 percent of revenue, with Oklahoma experiencing the lowest expected shortfall (2.39 percent) and Alaska witnessing the largest expected shortfall (41.56 percent). Six states have expected constant-revenue shortfalls in excess of 10 percent of revenue, while twenty-three states have expected shortfalls of less than 5 percent of revenue. As expected, states with the greatest (least) persistence in low-growth revenue regimes and more negative (less negative) recession growth rates experience larger (smaller) expected shortfalls. These estimates suggest that a modest rainy day fund balance equal to 5.25-6.5 percent of revenue

[16] The shortfalls for each state were computing using the point estimates for g_L, g_H, and P_{LL} that are the means of the posterior distributions (e.g. the estimates in Table 1). We explored the sensitivity of the shortfall figures by using random draws from the entire simulated posterior distributions in place of the posterior means and did not find significant differences in the shortfall values. One advantage of such a strategy is that it is quite simple to construct confidence intervals for the shortfall figures and savings rate figures that appear in Tables 2 and 3. We omitted confidence intervals simply to conserve space.

[17] The figures in the columns entitled "*Expected*" are computed as the mean of a discrete random variable, which is equal to the sum of each possible shortfall times the probability that the shortfall occurs.

would be sufficient for the typical state to maintain a constant level of revenue during a downturn.

Given that the trend-revenue shortfalls measure the amplitude of a shortfall as the difference between average expansion and contraction regimes, the trend-revenue shortfall figures are considerably larger than the constant-revenue values. In fact, the mean and median expected shortfalls across all states using the trend-revenue method are 13.2 and 16.5 percent of revenue respectively, compared to 5.25 and 6.5 percent using the constant-revenue approach. In addition, the expected trend-revenue shortfall values show that seventeen states experience shortfalls equal to at least 15 percent of revenue during a typical downturn and four states have expected shortfalls in excess of 20 percent of revenue. The state experiencing the smallest expected trend-revenue shortfall is Oklahoma (8.17 percent) and only seven states have expected trend-revenue shortfalls equal to 10 percent of revenue or less.

5.2 Savings rate rules

If you consider the difficulty in predicting recessions along with the magnitude of the shortfall figures presented in Table 2, the fiscal stress that states may expect to experience during a downturn can be substantial. While it is one thing for a policymaker to have an understanding of the likelihood of a given shortfall, it is quite another to develop a strategy to hedge against shortfalls because the duration of expansion regimes are also unknown. In this section of the paper we address this issue by deriving savings rate rules that policymakers may opt to follow to hedge against all of the possible expansion-contraction combinations that may occur in a given revenue cycle.

To construct the savings rate rules we examine the accumulated savings from an expansion lasting t_H periods, compare the accumulated savings to the shortfall that would prevail from a recession lasting t_L periods, and solve for the savings rate associated with that specific high-growth, low-growth combination. If this process is repeated for all possible expansion-contraction combinations, then we may construct a cumulative density function for savings rates. An x percent savings rate rule would then be the fraction of the level of revenue that must be saved during each expansion period to accumulate sufficient savings to offset x percent of all of the possible revenue cycles. We first derive the savings rate rules under the assumption of a constant-revenue shortfall and then extend the derivation to a trend-revenue shortfall.

If policymakers save a fraction of revenue (s) during each period of a high-growth regime, then at the end of one period revenue will be equal to $R_0\,(1+g_H)$ and the state's total savings will be $R_0\,s\,(1+g_H)$. After t_H periods of high-growth the state's accumulated savings, compounding at a rate r, may be written as:

$$R_0 s \sum_{j=1}^{t_H} (1+r)^{t_H-j+1}(1+g_H)^j \;. \tag{6}$$

When states save during expansion regimes, the shortfalls from Section 5.1 must be modified slightly. If revenue growth shifts to a low-growth regime, the shortfall in the first low-growth period will be the difference between the funds available for spending in the last high-growth period after saving a fraction s, $R_0(1+g_H)^{t_H}(1-s)$, and revenue in the first low-growth period, $R_0(1+g_H)^{t_H}(1+g_L)$. Assuming no additional savings in low-growth periods, the constant-revenue shortfall in the first low-growth period is given by $R_0\left[(1+g_H)^{t_H}(1-s)-(1+g_H)^{t_H}(1+g_L)\right]$, which is expressed as a share of revenue in the last high-growth period. If the downturn persists into a second period, then revenue will be equal to

$R_0(1+g_H)^{t_H}(1+g_L)^2$ and the shortfall will be $R_0\left[(1+g_H)^{t_H}(1-s)-(1+g_H)^{t_H}(1+g_L)^2\right]$. Thus, when states save a constant fraction s during each expansion period, the cumulative constant-revenue shortfall following t_L periods of low-growth is the sum of t_L similarly constructed terms and may be expressed as:

$$R_0\left[t_L(1+g_H)^{t_H}(1-s)-(1+g_H)^{t_H}\sum_{i=1}^{t_L}(1+g_L)^i\right]. \tag{7}$$

Since (6) is the state's accumulated savings from an expansion lasting t_H periods and (7) is the state's constant-revenue shortfall (with savings) from a recession lasting t_L periods, equating (6) and (7) and solving for s gives the fraction of current revenue that must be saved during each of the t_H high-growth periods to accumulate a rainy day fund balance equal to the constant-revenue shortfall lasting t_L periods.[18] This savings rate is given by:

$$s(t_H,t_L)=\frac{(1+g_H)^{t_H}\left[t_L-\sum_{i=1}^{t_L}(1+g_L)^i\right]}{\sum_{j=1}^{t_H}(1+r)^{t_H-j+1}(1+g_H)^j+t_L(1+g_H)^{t_H}}. \tag{8}$$

If the shortfall is measured as the difference between the average expansion and contraction, then the quantity of savings accumulated after an expansion lasting t_H periods will continue to be given by (6). However, the shortfall in the first low-growth period is now given by $R_0\left[(1+g_H)^{t_H+1}(1-s)-(1+g_H)^{t_H}(1+g_L)\right]$, which is the difference between what revenue would have been if the average expansion revenue growth continued (after saving a fraction s), $R_0(1+g_H)^{t_H+1}(1-s)$, and revenue in the first low-growth period, $R_0(1+g_H)^{t_H}(1+g_L)$. If the contraction continues into the second period, revenue will equal $R_0(1+g_H)^{t_H}(1+g_L)^2$ and the

[18] In a similar fashion to the shortfalls given in equations (4) and (5), we explored the sensitivity of the savings rates using random draws from the entire simulated posterior distributions in place of the posterior means. The results were not noticeably different from the results reported in the paper.

trend-revenue shortfall in just the second period is $R_0\left[(1+g_H)^{t_H+2}(1-s)-(1+g_H)^{t_H}(1+g_L)^2\right]$.

Thus, for a low-growth regime lasting t_L periods, the trend-revenue shortfall (with savings) may be written as:

$$R_0(1+g_H)^{t_H}\left[(1-s)\sum_{i=1}^{t_L}(1+g_H)^i-\sum_{i=1}^{t_L}(1+g_L)^i\right]. \tag{9}$$

Equating the accumulated savings and trend-revenue shortfall given by (6) and (9) and solving for s yields the savings rate that should be followed during each of the t_H high-growth periods to accumulate a rainy day fund balance equal to the trend-revenue shortfall lasting t_L periods. This rate can be shown to be:

$$s_2(t_H,t_L)=\frac{(1+g_H)^{t_H}\left[\sum_{i=1}^{t_L}(1+g_H)^i-(1+g_L)^i\right]}{\sum_{j=1}^{t_H}(1+r)^{t_H-j+1}(1+g_H)^j+(1+g_H)^{t_H}\sum_{i=1}^{t_L}(1+g_H)^i} \tag{10}$$

The constant- and trend-revenue savings rates in (8) and (10) apply to a specific (t_H, t_L) combination. Since the probability that a given regime will last exactly t_j periods is $P_j(t_j)=P_{jj}^{t_j-1}-P_{jj}^{t_j}$ for $j = H, L$, the probability that a high-growth regime lasting exactly t_H periods will be followed by a low-growth regime lasting exactly t_L periods is $P_H(t_H)\times P_L(t_L)$, assuming the high- and low-growth regime durations are independent. Thus, to determine the savings rate required during each year of an expansion that will be sufficient to guard against x percent of all possible expansion-contraction combinations, we construct a cumulative density function of savings rates on all of the possible (t_H, t_L) combinations under the assumption that $t_j = 1, 2, \ldots, 25$ for $j = H, L$ (in increments of .1).[19] The "*Expected*", "*75%*", and "*90%*" savings

[19] In short, we allow the duration of both an expansion and contraction to vary in length from 0.1 years to 25 years in increments of 0.1. This produces 250 different shortfall values (one from each of the possible 250 contractions) and 250 different levels of accumulated savings (one from each of the possible 250 expansions). The cumulative

rate estimates are presented in Table 3 for each state for the both constant- and trend-revenue shortfalls.

[Table 3 here]

It is important to note that while the shortfall values appearing in Table 2 depend on the distribution of contraction regimes, the savings rate figures in Table 3 depend on both the distribution of expansions and contractions. As a result, the 75 percent constant-revenue savings rate in a given state cannot be viewed as the savings rate necessary to accumulate savings equal to the state's 75 percent constant-revenue shortfall because the savings rates are a function of the uncertainty in both expansion and contraction durations, while the shortfalls depend only on the uncertainty in contractions.

If policymakers decided to follow the expected constant-revenue savings rate figure, then a state would accumulate sufficient savings (on average) during an expansion to maintain a constant level of revenue during a contraction. Of course, there will be times when a state will not have sufficient savings and there will also be times when the state will accumulate more savings than is required. On average however, if policymakers in Florida, for instance, saved 1.58 percent of revenue during each year of an expansion, then the state would be able to maintain a constant level of revenue in the next recession and would have zero reserves remaining at the end of the downturn.

Suppose for example that a policymaker in Nebraska wishes to be 75 percent certain her state can accumulate sufficient savings during expansions in order to maintain the average expansion growth rate in revenue during the next recession. Given the distribution of expansions

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density function for the savings rates is therefore constructed from the 62,500 possible expansion-contraction combinations. The state with the largest estimated P_{LL} is Alaska (= .60) and the state with largest estimated P_{HH} is North Carolina (= .81), so the probability that a recession will last 25 years in Alaska is equal to 0.0000002 and the probability that an expansion will last 25 years in North Carolina is 0.001.

and contractions in her state, saving 3.01 percent of the level of revenue during each expansion year would be sufficient to achieve her objective. If such an objective (which one could argue may be too risk-averse or politically unrealistic) were followed, then three out of every four recessions would have no impact on the state from the perspective of revenue growth. However, if policymakers save more than the expected savings rate rules, given either a constant-revenue or trend-revenue objective, then the state's accumulated reserves would be more than sufficient, on average, and states would end a contraction with a positive rainy day fund balance.

6. Conclusion

Economic slowdowns place tremendous pressure on state budgets and often require policymakers to enact unpopular expenditure reductions and/or tax increases. In this paper we estimate a Markov regime-switching regression of each state's total revenue growth over the past forty years to model the cyclical behavior of revenue expansions and contractions. This allows us to not only construct probability distributions of the revenue shortfalls states are likely to confront during recessions (including multi-year recessions), but also to construct savings rate rules that are based on the uncertainty inherent in both expansions and contractions. In short, the savings rate rules are the fraction of revenue that policymakers should save during each expansion period to hedge against all of the possible expansion-contraction combinations that may occur in their state with a given level of certainty. Our results have important implications for policymakers who wish to smooth cyclical fluctuations in revenue through the use of a rainy day fund or other type of savings instrument.

While we find that the typical state's expected revenue cycle lasts just over 6 years, the cycles vary in length from less than 5 to more than 7 years. For the typical state, the expected cycle consists of roughly 4.25 years of revenue expansion followed by 1.7 years of revenue contraction. Measuring shortfalls as the difference between the average expansion and average contraction, we find that the typical state can expect a revenue shortfall equal to 13 to 16 percent of revenue during a normal downturn. A representative state would, on average, build sufficient savings to offset such a shortfall by saving 3 to 3.5 percent of the level of revenue during each expansion period. In other words, if the typical state followed this rule, then the state would accumulate enough savings during an expansion to maintain the average expansion growth rate in revenue throughout a normal recession.

As with any empirical paper, the results should be viewed in context of our limitations. First, our estimates are based on revenue growth so a similar examination of each state's cyclical deficit, assuming such a measure could be meaningfully constructed, would provide a nice robustness check on our estimates. In addition, improvements in removing discretionary changes from revenue/expenditure data and updating the estimates as more data become available would be expected to alter the estimates that appear in the paper. We believe that the contribution of this paper does not lie in the establishment of a concrete set of estimates for each state, but rather in the application of the regime-switching methodology as a means of providing ongoing analysis that may be beneficial to policymakers.

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Table 1 – Markov Switching Parameter Estimates for State Total Revenue Growth

	$\hat{g}_H$	$\hat{g}_L$	$\hat{P}_{HH}$	$\hat{P}_{LL}$	$\hat{\sigma}_{\varepsilon}^2$	$E[tH]$	$E[tL]$	$E[tH] + E[tL]$	Concordance
Alabama	4.41	-3.51	0.72	0.37	24.66	3.54	1.59	5.13	0.77
Alaska	7.24	-9.45	0.75	0.60	68.06	3.99	2.52	6.51	0.88
Arizona	2.62	-2.05	0.76	0.40	19.24	4.20	1.66	5.86	0.74
Arkansas	4.13	-2.17	0.77	0.42	19.71	4.31	1.72	6.03	0.81
California	4.04	-2.88	0.76	0.44	21.91	4.10	1.77	5.88	0.77
Colorado	3.71	-5.49	0.75	0.41	27.64	4.07	1.69	5.76	0.74
Connecticut	4.34	-2.26	0.78	0.40	19.68	4.57	1.67	6.24	0.88
Delaware	3.70	-1.87	0.77	0.39	18.86	4.34	1.63	5.97	0.84
Florida	3.72	-3.27	0.79	0.48	21.36	4.74	1.92	6.66	0.84
Georgia	3.68	-2.30	0.77	0.42	20.07	4.32	1.73	6.05	0.84
Hawaii	3.94	-3.87	0.77	0.55	21.81	4.36	2.24	6.60	0.93
Idaho	3.59	-2.98	0.77	0.42	21.13	4.35	1.74	6.09	0.74
Illinois	3.64	-1.64	0.78	0.39	17.85	4.52	1.64	6.16	0.91
Indiana	3.93	-1.78	0.77	0.40	18.63	4.32	1.68	6.00	0.84
Iowa	3.69	-2.21	0.78	0.40	19.79	4.49	1.66	6.15	0.79
Kansas	4.02	-3.16	0.76	0.39	22.23	4.15	1.63	5.79	0.81
Kentucky	4.68	-2.70	0.74	0.44	21.93	3.80	1.79	5.59	0.86
Louisiana	3.29	-2.78	0.75	0.40	21.02	4.01	1.67	5.69	0.72
Maine	4.27	-3.11	0.78	0.42	21.86	4.53	1.74	6.27	0.84
Maryland	3.93	-2.75	0.76	0.41	21.06	4.22	1.70	5.91	0.79
Massachusetts	4.11	-2.02	0.78	0.40	19.31	4.44	1.67	6.11	0.86
Michigan	4.45	-4.24	0.74	0.41	23.23	3.80	1.71	5.51	0.86
Minnesota	5.16	-7.32	0.76	0.35	26.33	4.26	1.55	5.80	0.95
Mississippi	4.55	-3.09	0.77	0.42	22.13	4.39	1.72	6.11	0.86
Missouri	4.23	-2.39	0.76	0.41	20.44	4.13	1.70	5.83	0.79
Montana	3.28	-1.66	0.77	0.40	17.79	4.33	1.66	5.99	0.84
Nebraska	4.50	-2.21	0.75	0.41	20.78	4.03	1.69	5.72	0.79
Nevada	2.55	-3.18	0.79	0.44	20.24	4.70	1.77	6.48	0.81
New Hampshire	3.38	-2.19	0.76	0.43	19.63	4.21	1.75	5.95	0.77
New Jersey	5.01	-2.24	0.76	0.43	21.38	4.23	1.77	6.00	0.86
New Mexico	3.91	-3.60	0.74	0.39	23.04	3.78	1.65	5.43	0.79
New York	4.27	-1.85	0.78	0.42	18.42	4.48	1.73	6.22	0.93
North Carolina	4.08	-3.90	0.81	0.50	20.49	5.15	2.00	7.14	0.84
North Dakota	3.63	-2.23	0.76	0.39	20.52	4.09	1.64	5.73	0.81
Ohio	3.57	-1.89	0.77	0.38	18.72	4.43	1.62	6.05	0.77
Oklahoma	3.27	-1.39	0.76	0.39	16.88	4.21	1.64	5.85	0.95
Oregon	4.32	-5.02	0.74	0.43	25.97	3.88	1.74	5.62	0.84
Pennsylvania	3.89	-2.96	0.76	0.42	22.05	4.15	1.73	5.88	0.88
Rhode Island	4.23	-2.18	0.76	0.41	20.19	4.11	1.70	5.81	0.88
South Carolina	4.17	-2.06	0.79	0.41	19.29	4.66	1.69	6.34	0.91
South Dakota	3.69	-2.59	0.75	0.37	20.82	3.92	1.58	5.50	0.77
Tennessee	3.97	-2.60	0.76	0.40	21.07	4.09	1.66	5.74	0.74
Texas	4.37	-3.98	0.79	0.44	23.01	4.72	1.78	6.50	0.86
Utah	4.15	-3.94	0.74	0.42	24.64	3.83	1.72	5.55	0.88
Vermont	4.31	-2.91	0.75	0.48	21.86	4.06	1.94	6.00	0.86
Virginia	4.02	-2.99	0.78	0.42	21.06	4.48	1.73	6.22	0.86
Washington	3.46	-4.09	0.78	0.41	21.44	4.61	1.69	6.30	0.88
West Virginia	3.96	-1.83	0.77	0.40	18.73	4.40	1.67	6.07	0.84
Wisconsin	5.99	-8.60	0.69	0.35	40.07	3.23	1.54	4.76	0.88
Wyoming	3.46	-2.91	0.80	0.48	19.47	5.01	1.92	6.94	0.91
Mean	**4.05**	**-3.13**	**0.76**	**0.42**	**22.35**	**4.25**	**1.73**	**5.99**	**0.84**
Median	**3.99**	**-2.77**	**0.76**	**0.41**	**21.04**	**4.24**	**1.70**	**5.99**	**0.84**
Maximum	**7.24**	**-1.39**	**0.81**	**0.60**	**68.06**	**5.15**	**2.52**	**7.14**	**0.95**
Minimum	**2.55**	**-9.45**	**0.69**	**0.35**	**16.88**	**3.23**	**1.54**	**4.76**	**0.72**

Notes: g_H is the high-growth regime mean growth rate and g_L is the low-growth regime mean growth rate. p_{HH} is the probability of staying in the high-growth regime next period conditional on being in the high-growth regime this period; p_{LL} is the probability of being in the low-growth regime next period conditional on being in the low-growth regime this period. $E(t_H)$ and $E(t_L)$ denote the expected duration of revenue growth expansion periods and contraction periods.

Figure 1 – Cumulative Density Functions of Revenue Shortfalls
(Assumes g_H = 3.99, g_L = -2.77, P_{HH} = .76, and P_{LL} = 0.41)

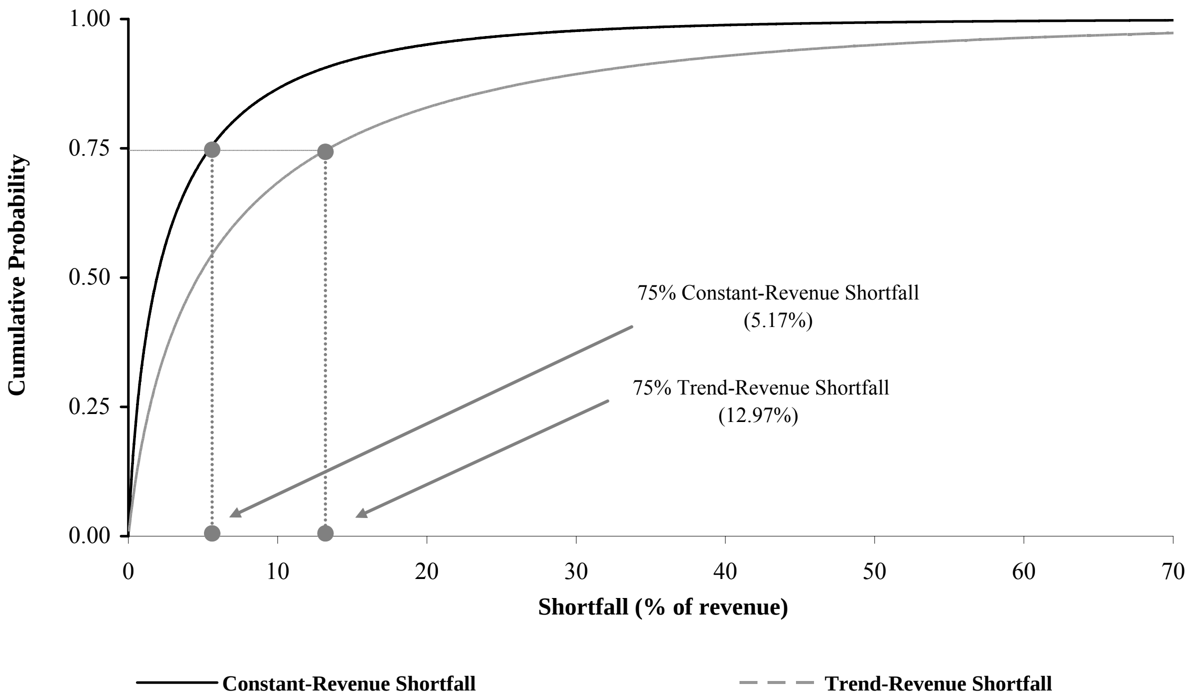


Table 2 – Shortfall Distributions of State Revenue Contractions
(figures expressed as a percentage of revenue)

	Constant-Revenue Shortfall			Trend-Revenue Shortfall		
	Expected	*75%*	*90%*	*Expected*	*75%*	*90%*
Alabama	5.53	6.54	14.09	12.80	14.87	32.44
Alaska	41.56	47.49	108.77	82.43	87.73	210.58
Arizona	3.64	4.25	8.89	8.44	9.74	20.52
Arkansas	4.24	4.50	10.72	12.64	13.15	31.82
California	6.02	6.56	15.05	14.92	15.92	37.07
Colorado	10.07	11.29	24.94	17.30	19.06	42.63
Connecticut	4.07	4.69	10.47	12.22	13.80	31.26
Delaware	3.18	3.50	8.11	9.69	10.48	24.60
Florida	8.30	8.92	21.44	18.37	19.28	47.13
Georgia	4.57	5.25	11.35	12.21	13.77	30.12
Hawaii	14.08	15.49	35.59	29.87	31.86	74.69
Idaho	5.93	6.79	14.64	13.43	15.11	32.96
Illinois	2.83	3.07	7.11	9.34	9.94	23.35
Indiana	3.24	3.68	8.23	10.68	11.91	26.99
Iowa	3.93	4.58	9.58	10.74	12.32	26.03
Kansas	5.34	5.89	13.61	12.43	13.47	31.53
Kentucky	5.78	6.15	14.99	16.41	17.02	42.27
Louisiana	5.04	5.76	12.84	11.24	12.65	28.51
Maine	6.18	7.09	15.27	15.12	16.98	37.10
Maryland	5.16	5.70	12.70	12.86	13.94	31.50
Massachusetts	3.62	4.19	9.36	11.28	12.80	29.00
Michigan	7.97	8.74	20.66	16.86	18.08	43.45
Minnesota	10.49	12.18	26.92	18.37	20.91	46.94
Mississippi	5.95	6.39	15.18	15.18	15.95	38.51
Missouri	4.49	4.95	11.05	12.80	13.83	31.31
Montana	2.94	3.11	7.21	8.93	9.29	21.79
Nebraska	4.08	4.57	10.20	12.79	14.01	31.76
Nevada	6.66	7.25	16.60	12.24	13.14	30.38
New Hampshire	4.44	5.00	11.49	11.58	12.82	29.86
New Jersey	4.67	5.11	11.76	15.70	16.73	39.19
New Mexico	6.22	6.72	15.48	13.31	14.10	32.93
New York	3.69	4.23	9.16	12.58	14.13	31.00
North Carolina	10.87	11.55	28.27	23.16	23.96	59.81
North Dakota	3.84	4.17	9.66	10.33	11.03	25.85
Ohio	3.14	3.52	7.63	9.28	10.26	22.44
Oklahoma	2.39	2.60	6.03	8.17	8.76	20.56
Oregon	9.90	11.39	24.38	18.99	21.40	46.47
Pennsylvania	5.84	6.74	14.53	13.90	15.74	34.37
Rhode Island	4.13	4.51	10.74	12.53	13.38	32.38
South Carolina	3.80	4.26	9.52	11.85	13.01	29.48
South Dakota	4.00	4.34	9.73	9.88	10.57	23.95
Tennessee	4.57	4.85	11.22	11.84	12.34	28.92
Texas	8.33	9.05	20.67	18.09	19.18	44.54
Utah	7.63	8.13	19.24	16.12	16.82	40.44
Vermont	7.63	8.66	19.16	19.70	21.78	49.08
Virginia	5.92	6.82	14.69	14.28	16.13	35.24
Washington	7.57	8.45	18.75	14.30	15.70	35.25
West Virginia	3.29	3.80	8.50	10.67	12.09	27.40
Wisconsin	11.86	14.29	29.25	20.73	24.43	50.83
Wyoming	7.48	7.96	19.17	16.89	17.58	42.99
Mean	**6.52**	**7.29**	**16.49**	**15.31**	**16.66**	**38.38**
Median	**5.25**	**5.83**	**13.22**	**12.80**	**14.05**	**32.10**
Maximum	**41.56**	**47.49**	**108.77**	**82.43**	**87.73**	**210.58**
Minimum	**2.39**	**2.60**	**6.03**	**8.17**	**8.76**	**20.52**

Table 3 – Savings Rate Distributions of State Revenue Cycles
(figures expressed as a percentage of revenue)

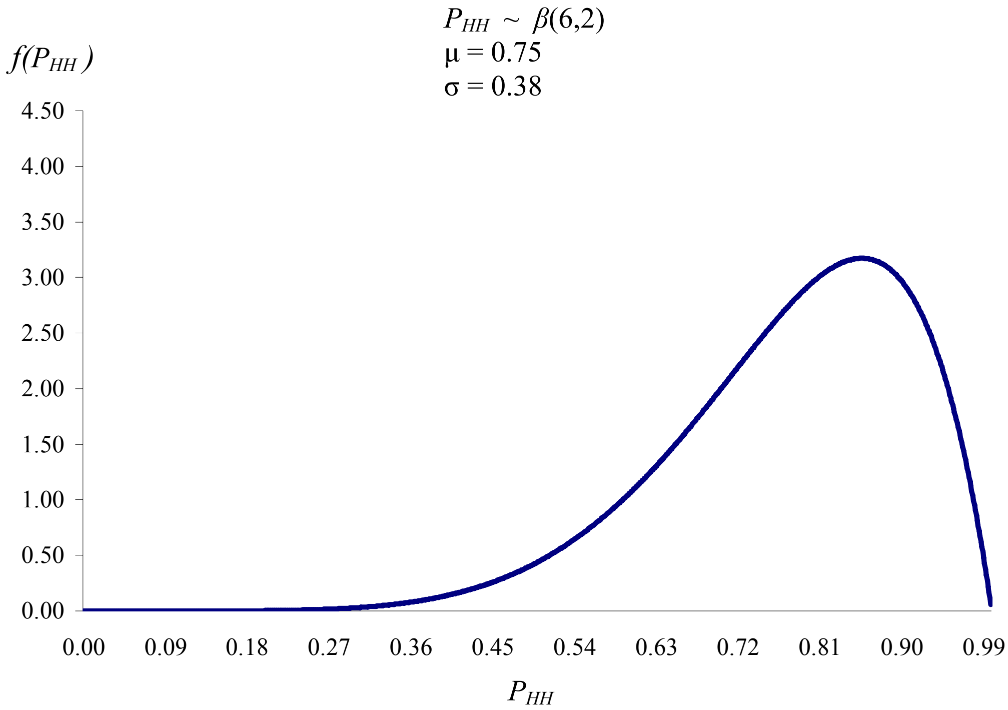
	Constant Revenue Shortfall Savings Rates			Trend Revenue Shortfall Savings Rates		
	Expected	*75%*	*90%*	*Expected*	*75%*	*90%*
Alabama	1.45	2.02	3.56	3.44	4.72	8.52
Alaska	6.88	9.90	16.74	15.64	20.23	38.59
Arizona	0.84	1.16	2.12	1.97	2.68	4.98
Arkansas	0.93	1.30	2.36	2.83	3.83	7.14
California	1.32	1.84	3.30	3.34	4.57	8.39
Colorado	2.33	3.27	5.82	4.20	5.69	10.58
Connecticut	0.90	1.25	2.30	2.74	3.72	7.04
Delaware	0.74	1.02	1.86	2.26	3.09	5.74
Florida	1.58	2.21	4.05	3.61	4.88	9.22
Georgia	1.00	1.38	2.52	2.71	3.68	6.84
Hawaii	2.42	3.39	6.07	5.36	7.20	13.48
Idaho	1.29	1.79	3.26	2.99	4.05	7.56
Illinois	0.64	0.88	1.63	2.12	2.88	5.43
Indiana	0.73	1.01	1.85	2.43	3.31	6.16
Iowa	0.88	1.22	2.24	2.44	3.32	6.24
Kansas	1.26	1.75	3.19	3.01	4.07	7.57
Kentucky	1.30	1.81	3.21	3.76	5.11	9.32
Louisiana	1.18	1.65	2.94	2.68	3.68	6.71
Maine	1.32	1.85	3.37	3.31	4.49	8.43
Maryland	1.17	1.63	2.93	2.96	4.05	7.50
Massachusetts	0.81	1.12	2.08	2.56	3.45	6.53
Michigan	1.89	2.64	4.66	4.13	5.57	10.22
Minnesota	2.63	3.66	6.64	4.87	6.51	12.40
Mississippi	1.31	1.83	3.32	3.42	4.64	8.66
Missouri	1.02	1.43	2.57	2.97	4.03	7.46
Montana	0.67	0.92	1.70	2.05	2.78	5.22
Nebraska	0.95	1.32	2.37	3.01	4.08	7.54
Nevada	1.36	1.90	3.49	2.58	3.50	6.63
New Hampshire	0.97	1.35	2.44	2.57	3.52	6.51
New Jersey	1.02	1.40	2.55	3.45	4.70	8.65
New Mexico	1.53	2.14	3.77	3.35	4.59	8.34
New York	0.79	1.11	2.02	2.73	3.71	6.93
North Carolina	1.93	2.72	5.02	4.28	5.81	11.15
North Dakota	0.91	1.26	2.29	2.48	3.38	6.25
Ohio	0.72	1.01	1.85	2.16	2.94	5.51
Oklahoma	0.56	0.77	1.41	1.92	2.61	4.84
Oregon	2.28	3.20	5.66	4.57	6.20	11.38
Pennsylvania	1.30	1.80	3.26	3.17	4.31	7.96
Rhode Island	0.94	1.30	2.36	2.89	3.92	7.25
South Carolina	0.83	1.14	2.12	2.60	3.51	6.68
South Dakota	1.01	1.40	2.52	2.53	3.43	6.36
Tennessee	1.07	1.49	2.69	2.83	3.85	7.10
Texas	1.72	2.39	4.40	3.85	5.21	9.92
Utah	1.78	2.47	4.40	3.88	5.28	9.68
Vermont	1.54	2.15	3.83	4.07	5.52	10.22
Virginia	1.27	1.78	3.24	3.14	4.26	7.99
Washington	1.65	2.29	4.22	3.22	4.34	8.26
West Virginia	0.74	1.03	1.89	2.43	3.28	6.17
Wisconsin	3.45	4.88	8.34	6.45	8.73	15.75
Wyoming	1.39	1.93	3.60	3.21	4.35	8.32
Mean	**1.40**	**1.96**	**3.52**	**3.42**	**4.63**	**8.63**
Median	**1.22**	**1.70**	**3.06**	**3.00**	**4.06**	**7.55**
Maximum	**6.88**	**9.90**	**16.74**	**15.64**	**20.23**	**38.59**
Minimum	**0.56**	**0.77**	**1.41**	**1.92**	**2.61**	**4.84**

Appendix A – Actual Versus Policy-Reduced Revenue Growth Comparison

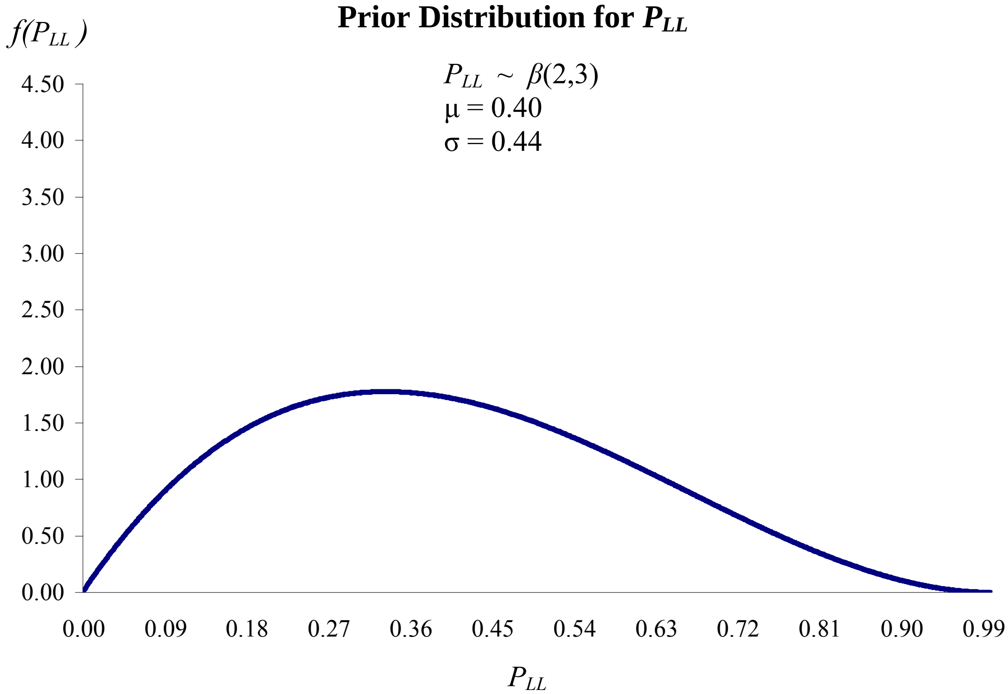
	Mean growth rate during positive-growth periods		**Mean growth rate during negative-growth periods**		**% positive periods occurring in back-to-back years**		**% negative periods occurring in back-to-back years**	
	Actual data	*Policy reduced*	*Actual data*	*Policy reduced*	*Actual data*	*Policy reduced*	*Actual data*	*Policy reduced*
AL	5.60	5.98	-4.40	-2.98	0.73	0.70	0.20	0.38
AK	18.11	12.86	-12.57	-11.38	0.48	0.70	0.40	0.56
AZ	5.18	3.42	-4.30	-2.62	0.68	0.75	0.40	0.27
AR	5.91	4.63	-2.86	-1.67	0.68	0.86	0.25	0.50
CA	5.75	5.17	-3.93	-2.45	0.74	0.74	0.42	0.42
CO	5.14	5.42	-7.07	-5.02	0.72	0.72	0.27	0.50
CT	6.84	4.80	-5.16	-2.61	0.75	0.86	0.36	0.33
DE	6.11	4.17	-2.97	-2.09	0.62	0.83	0.21	0.14
FL	5.80	4.52	-4.58	-2.75	0.80	0.75	0.54	0.36
GA	4.91	4.16	-4.63	-2.51	0.79	0.83	0.33	0.38
HI	5.04	4.97	-3.95	-3.17	0.77	0.79	0.54	0.64
ID	5.55	4.59	-4.28	-3.26	0.70	0.78	0.31	0.36
IL	5.31	3.60	-4.91	-1.10	0.79	0.87	0.33	0.00
IN	4.75	4.27	-3.48	-1.02	0.86	0.86	0.43	0.43
IA	4.68	4.56	-4.14	-2.72	0.80	0.82	0.13	0.33
KS	5.49	4.94	-3.89	-3.00	0.66	0.82	0.09	0.40
KY	5.97	5.29	-4.63	-2.97	0.74	0.80	0.11	0.25
LA	4.77	4.70	-3.18	-3.02	0.63	0.73	0.23	0.46
ME	6.29	5.02	-5.02	-2.72	0.78	0.82	0.45	0.44
MD	6.18	4.98	-3.39	-2.50	0.76	0.78	0.57	0.45
MA	6.15	4.48	-6.26	-2.15	0.82	0.86	0.44	0.33
MI	6.81	6.37	-5.49	-3.71	0.67	0.66	0.31	0.36
MN	6.75	6.67	-6.18	-7.22	0.75	0.76	0.36	0.30
MS	6.42	5.33	-3.57	-3.79	0.81	0.86	0.50	0.38
MO	5.55	5.06	-3.21	-2.33	0.82	0.76	0.50	0.22
MT	4.66	3.53	-2.16	-1.20	0.71	0.83	0.25	0.29
NE	6.58	5.15	-2.47	-1.10	0.70	0.76	0.38	0.22
NV	5.43	3.44	-3.92	-4.08	0.52	0.81	0.33	0.45
NH	6.52	4.05	-4.01	-2.19	0.63	0.76	0.38	0.30
NJ	7.52	5.20	-5.00	-1.10	0.78	0.86	0.45	0.33
NM	5.90	5.40	-5.31	-3.29	0.65	0.63	0.17	0.23
NY	6.45	4.18	-3.18	-1.75	0.77	0.95	0.50	0.67
NC	5.76	5.53	-3.60	-3.07	0.80	0.83	0.46	0.54
ND	6.24	4.24	-4.76	-2.91	0.63	0.77	0.23	0.13
OH	4.87	4.49	-4.94	-1.72	0.80	0.82	0.13	0.50
OK	4.74	3.01	-2.74	-0.86	0.66	0.93	0.09	0.00
OR	6.84	5.80	-6.00	-4.59	0.66	0.70	0.29	0.38
PA	6.13	4.56	-3.71	-4.26	0.69	0.77	0.43	0.13
RI	6.44	4.61	-3.74	-2.63	0.74	0.84	0.42	0.17
SC	4.55	4.30	-3.52	-3.09	0.84	0.90	0.00	0.00
SD	5.75	4.94	-4.40	-2.96	0.61	0.66	0.08	0.09
TN	5.15	5.14	-3.46	-2.00	0.79	0.71	0.40	0.25
TX	6.13	5.45	-5.22	-4.10	0.75	0.79	0.27	0.30
UT	6.35	5.34	-4.55	-4.59	0.66	0.75	0.29	0.36
VT	6.39	4.99	-3.39	-1.40	0.66	0.81	0.36	0.58
VA	5.31	4.87	-6.24	-3.30	0.77	0.82	0.13	0.44
WA	4.93	4.79	-5.49	-5.10	0.78	0.81	0.36	0.45
WV	4.69	4.37	-2.96	-1.30	0.81	0.86	0.00	0.29
WI	8.58	9.53	-10.14	-8.17	0.71	0.68	0.33	0.47
WY	6.17	4.12	-4.21	-2.62	0.68	0.88	0.40	0.70
Mean	**6.06**	**5.02**	**-4.54**	**-3.08**	**0.72**	**0.79**	**0.32**	**0.35**
Median	**5.85**	**4.84**	**-4.24**	**-2.74**	**0.74**	**0.80**	**0.33**	**0.36**

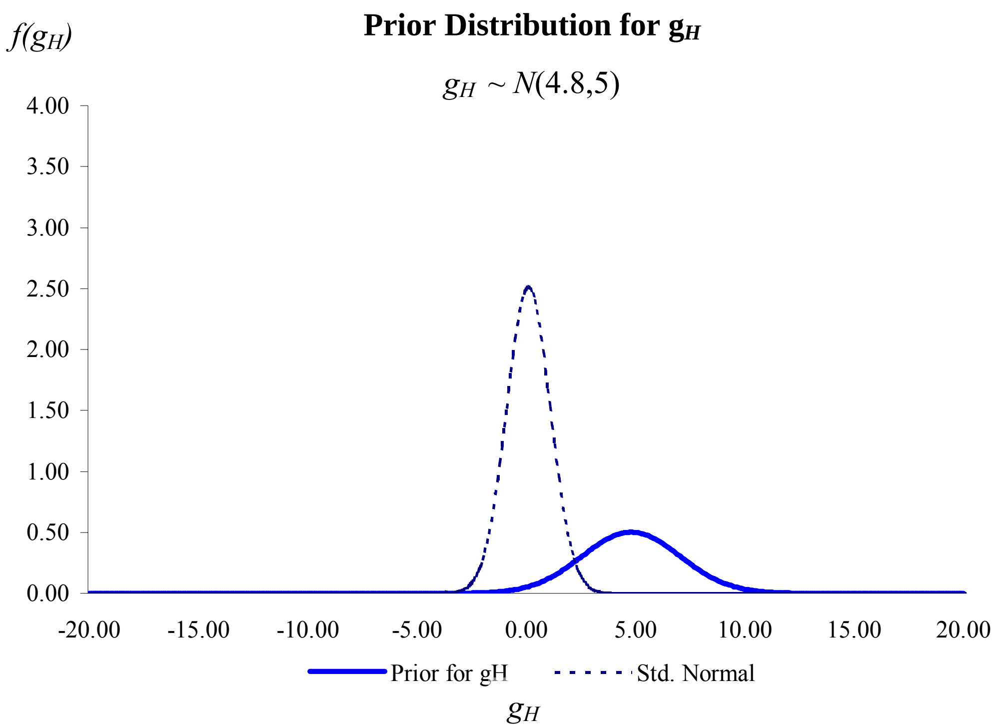
Appendix B – Graphical Illustration of Prior Distributions

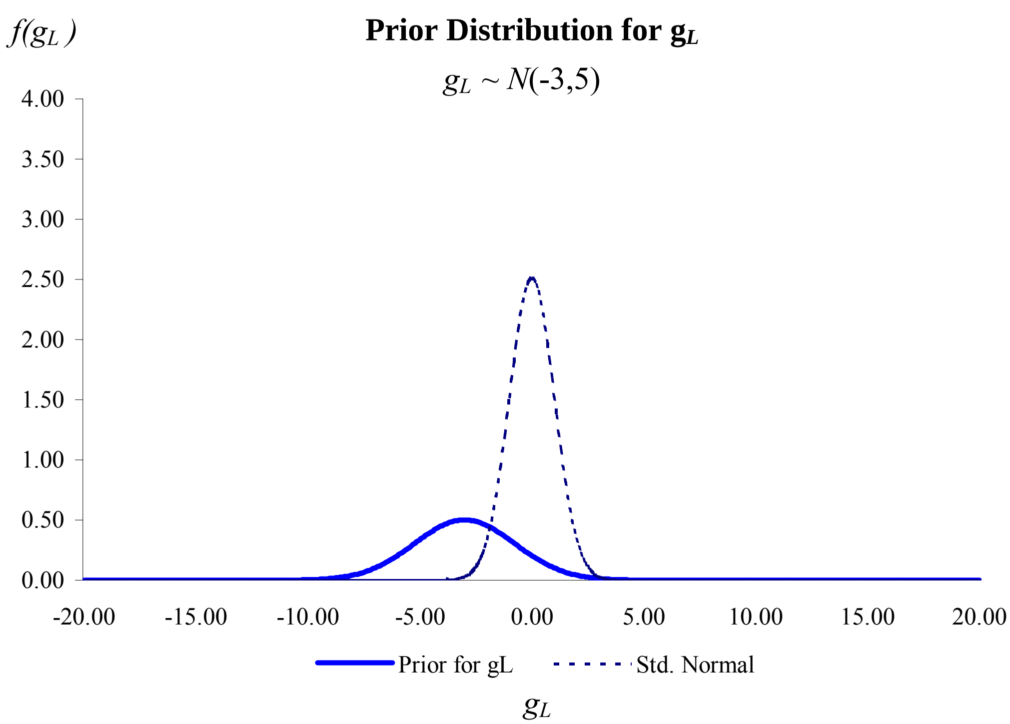
Prior Distribution for P_{HH}



Prior Distribution for P_{LL}




Prior Distribution for g_H
$g_H \sim N(4.8,5)$
$f(g_H)$
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
-20.00
-15.00
-10.00
-5.00
0.00
5.00
10.00
15.00
20.00
Prior for gH
Std. Normal
g_H


Prior Distribution for g_L
$g_L \sim N(-3,5)$
$f(g_L)$
4.00
3.50
3.00
2.50
2.00
1.50
1.00
0.50
0.00
-20.00
-15.00
-10.00
-5.00
0.00
5.00
10.00
15.00
20.00
Prior for gL
Std. Normal
g_L