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A state-level analysis of the Great Moderation ☆

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ABSTRACT

A number of studies have documented a reduction in aggregate macroeconomic volatility beginning in the early 1980s, i.e., the "Great Moderation." This paper documents the Great Moderation at the state level, finding significant heterogeneity in the timing and magnitude of states' structural breaks. For example, we find that 14 states had breaks that occurred at least three years before or after the aggregate break, while another 11 states did not experience any statistically important break during the period. Volatility reductions were positively related to the initial level of volatility, durable-goods share, and per capita energy consumption; and negatively related to average firm size, bank-branch deregulation, and increases in the share with a high school diploma. The probability of a state experiencing a break was associated with nondurable-goods share, energy consumption, and demographics. We use these results to examine the plausibility of several explanations of the Great Moderation.

1. Introduction

The U.S. economy has experienced a number of dramatic changes during the post-War period. One of these changes—a decline in the volatility of a broad range of macroeconomic variables—occurred in the early 1980s. Researchers have documented the presence of structural breaks in the volatility of a number of national time series, including GDP (Kim and Nelson, 1999a; McConnell and Perez-Quiros, 2000), consumption (Chauvet and Potter, 2001), and prices (Stock and Watson, 2003). Blanchard and Simon (2001) also find a significant reduction in the volatility of output, although they consider the reduction as a long-term trend rather than as a structural break.[1] So pervasive is the evidence for an aggregate volatility reduction that, in a speech on February 20, 2004, at the Eastern Economic Association Meetings, then-Federal Reserve governor Ben Bernanke described the phenomenon as "The Great Moderation."

In this paper, we examine the Great Moderation using a state-level empirical business cycle model that allows for state-specific volatility reductions. Our approach follows Owyang et al. (2005), who used an empirical model based on the Markov-switching model of Hamilton (1989) to examine cross-sectional variation in the timing and magnitude of state-level business cycles. They found that state business cycles, though similar to the national cycle, exhibited idiosyncratic characteristics that depended on demographics and industrial composition. We document the timing and size of the state-level volatility reductions by adapting their approach to allow for structural breaks.

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[1] Stock and Watson (2003) argue that "the evidence better supports the 'break' rather than the 'trend' characterization" of the volatility reduction.

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We find significant variation in both the timing and the magnitude of states' volatility reductions: While 14 states had breaks that occurred at least three years before or after the aggregate break, another 11 states did not experience statistically important breaks (i.e., the model with the break did not differ greatly from the model without a break). The states that do not appear to have experienced a break tended to be in the East and, as the list includes New York, are not small states only. The states with the largest volatility reductions associated with the structural breaks were scattered across the Mountain region, the upper Midwest/Great Lakes area, and the Ohio and Mississippi valleys. The smallest volatility reductions tended to be for states along the Eastern Seaboard.[2]

This cross-section of structural breaks provides us with a large number of volatility reductions to study, rather than the single national-level event that is usually considered. Because the magnitude and timing of states' structural breaks were associated with several state-level characteristics, our results are useful in sorting through the various hypotheses about the causes of the Great Moderation. More specifically, volatility reductions were largest in states with relatively high initial levels of volatility, high concentrations in durable-goods industries, and/or high average energy consumption. They were smallest in states with high average firm size, bank-branch deregulation, and increases in the share with a high school diploma. Large concentrations in nondurables tended to mean a lower probability of a break, as did high average energy consumption. On the other hand, the presence of large firms or a large share of young workers tended to mean a higher probability of a break. As we will argue, this set of results suggests that only one of the five main hypotheses about the Great Moderation—improved monetary policy—is consistent with the pattern of state-level volatility reductions.

The remainder of the paper is as follows: Section 2 examines the evidence for a reduction in the volatility of aggregate employment. Section 3 performs a similar exercise but at the state level. Section 4 considers a list of possible covariates for the characteristics of states' structural breaks. Section 5 concludes.

2. The volatility reduction in aggregate employment

Many recent papers have discussed the nature of the volatility reduction in aggregate Gross Domestic Product (GDP) and other variables. We will use employment data because of a lack of a suitable alternative to GDP series at the state level. Although Gross State Product series are available, their yearly frequency makes them unsuitable because an entire business cycle event such as a recession can occur within a single calendar year. For this and subsequent sections, the data we use are seasonally adjusted, monthly payroll employment from the Bureau of Labor Statistics. Each of the models is estimated in annualized growth rates. To ease comparison between the national and state-level models, the aggregate model is estimated using the growth rate constructed from the sum of the levels of the 48 contiguous states and the District of Columbia. All series extend from 1956:02 through 2004:12.

2.1. The model

Our model is a straightforward extension of the Markov-switching model of Hamilton (1989) in which we suppress the autoregressive dynamics for simplicity. A benefit of the Markov-switching model is its explicit representation of business cycle phases.[3] In addition, we allow for the possibility of a structural break in the regime-dependent steady-state growth rates of employment as well as the conditional variance of employment. Let Y_t reflect the growth rate of aggregate employment; then,

$$Y_t = \left(\mu_{0,A} + \mu_{1,A} S_t\right)(1-D_t) + \left(\mu_{0,B} + \mu_{1,B} S_t\right) D_t + \eta_t, \tag{1}$$

where $\eta_t \sim N(0,\ \sigma_A^2(1-D_t)+\sigma_B^2 D_t)$, σ_A^2 and σ_B^2 are regime-dependent conditional variances, and D_t is a dummy variable that indicates the timing of the structural break τ such that $D_t=0$ when $t<\tau$, and 1 otherwise.

Within a regime, employment can grow at one of two rates, $\mu_{0,j}$ or μ_{1j}, which might be thought of as recession and expansion growth rates. The pattern of recession and expansion is governed by a first-order hidden Markov variable S_t, which has transition probabilities

$$P(S_t = 0 | S_{t-1} = 0) = q_A(1-D_t) + q_B D_t,$$
$$P(S_t = 1 | S_{t-1} = 1) = p_A(1-D_t) + p_B D_t,$$

which also are subject to the structural break.

2.2. Estimation

The model in the preceding subsection is estimated using Bayesian techniques via the Gibbs sampler (Gelfand and Smith, 1990).[4] Bayesian estimation requires prior distributions chosen by the econometrician. In this case, we assume that (i) the vector of conditional

[2] We should point out concurrent work by Carlino et al. (2007) that also uses state-level employment data to examine the post-War reduction in volatility. The fundamental difference between their paper and ours is that they are interested in volatility reduction as a long-term trend (à la Blanchard and Simon, 2001) rather than as a structural break. Like us, however, they allow for state-specific structural breaks and find significant variation. See also Carlino et al. (2005).

[3] An alternate approach to our strategy is employed by Ahmed et al. (2004), who perform a spectral decomposition of some aggregate macroeconomic series.

[4] The Gibbs sampler is a Markov-chain Monte Carlo procedure in which the joint distribution for all parameters is obtained via sampling from the conditional distributions of each parameter. Repeated iterations of draws from the individual conditional densities produce a collection of draws that form the ergodic distribution for the full set of parameters, including the break date τ.

mean parameters λ has a multivariate normal prior distribution, (ii) each conditional variance has an inverse gamma prior distribution, and (iii) each transition probability has a beta prior distribution. Each distribution is parameterized to yield a proper, yet diffuse, prior. To capture the volatility reduction, we assume the break parameter τ has a discrete uniform prior distribution over all possible break dates. Given these prior distributions, estimation using the Gibbs sampler is straightforward. The hidden Markov variable is drawn from the procedure discussed in Kim and Nelson (1999b). Conditional on the draws for the parameter vectors and the hidden Markov variable, the posterior distribution for candidate break dates is multinomial with probabilities that are proportional to the model likelihood function (Carlin et al., 1992).

To evaluate the evidence in favor of the model with a structural break, we estimate the model above without the structural break, denoted M_0, and with the structural break, denoted M_1, and then compute the marginal data density; $p(Y|M_j)$, $j=0,1$; for each model. The evidence in favor of M_1 is then summarized by the Bayes Factor:

$$B_{10} = \frac{p(Y|M_1)}{p(Y|M_0)}.$$

Jeffreys (1961) provides a log scale for the interpretation of B_{10} given as

$\ln(B_{10})<0$	M_0 preferred
$0<\ln(B_{10})<1.2$	Very slight evidence in favor of M_1
$1.2<\ln(B_{10})<2.3$	Slight evidence in favor of M_1
$2.3<\ln(B_{10})<4.6$	Strong evidence in favor of M_1
$\ln(B_{10})>4.6$	Decisive evidence in favor of M_1

Intuition for the Jeffreys scale can be obtained by noting that with equal prior probability given to M_0 and M_1, so that $p(M_0)=p(M_1)$, the Bayes Factor is equivalent to the posterior odds in favor of M_1:

$$B_{10} = \frac{p(M_1|Y)}{p(M_0|Y)}.$$

Thus, "strong" evidence on the Jeffreys scale indicates that model M_1 is deemed to be $e^{2.3}\approx 10$ times (or greater) more likely than M_0.

2.3. Results

Estimation yields a number of results that confirm the presence of a volatility reduction in aggregate employment (see Table 1). The posterior median of the break date is September 1984, and the 5th and 95th percentiles of the break date are March 1984 and May 1985.[5] The log Bayes factor in favor of the model with a break versus the model with no break is 20.9, providing decisive evidence of a structural break using the Jeffreys scale. Moreover, the break affects several aspects of the aggregate employment process, corresponding to a reduction in σ^2 (reduction in residual variance), a decline in the absolute value of both μ_0 and μ_1 (recessions are less severe; expansions are less robust), and an increase in both p and q (business cycle phases last longer). The ratio of the post- to pre-break unconditional standard deviation of Y_t has a posterior median of 0.573, with 5th and 95th posterior percentiles of 0.572 and 0.582. Thus, the structural break corresponds to a roughly 43% reduction in the volatility of Y_t. With these results in mind, we decompose the aggregate volatility reduction into its state-level elements.

3. State-level volatility reductions

In this section, we modify the Hamilton model outlined above to account for the possibility that states' structural breaks differed in timing and magnitude from each others' and from the aggregate break.

3.1. Model

The model for an individual state i's employment growth rate is analogous to the model for aggregate employment growth:

$$y_{it} = \left(\mu_{i0,A} + \mu_{i1,A}S_{it}\right)(1-D_{it}) + \left(\mu_{i0,B} + \mu_{i1,B}S_{it}\right)D_{it} + \eta_{it},$$

where $\eta_{it}\sim N(0,\sigma_{i,A}{}^2(1-D_{it})+\sigma_{i,B^2Dit})$. The state-level transition probabilities are

$$P(S_{it} = 0|S_{it-1} = 0) = q_{i,A}(1-D_{it}) + q_{i,B}D_{it} \text{ and}$$
$$P(S_{it} = 1|S_{it-1} = 1) = p_{i,A}(1-D_{it}) + p_{i,B}D_{it},$$

and $D_{it}=0$ when $t<\tau_i$, and 1 otherwise.

[5] McConnell and Perez-Quiros (2000) document the structural break in volatility of GDP in the first quarter of 1984. Not surprisingly, the median volatility reduction in aggregate employment occurs slightly later. All break dates cited in the literature, however, lie within the 5th and 95th percentiles of the posterior distribution for our aggregate employment break.

Table 1
Results for aggregate employment

Log Bayes factor	20.9
Break Date	
Posterior median	September 1984
5th and 95th percentiles	March 1984, May 1985
Volatility Ratio	
Posterior median	0.573
5th and 95th percentiles	0.572, 0.582

Here, we have assumed that each state has an idiosyncratic business cycle governed by its own hidden Markov variable S_{it}. Further, each state is allowed to experience a volatility reduction with idiosyncratic timing τ_i. To focus on the breaks associated with the volatility reduction, τ_i is restricted to be within ten years on either side of the posterior median of the aggregate break date, i.e., between October 1974 and August 1994. Estimation for each state is as described in the previous section. As above, we estimate the model with and without a break to determine the likelihood of a break in all parameters.

3.2. Results

To highlight the geographic dimension of our results, we present them in maps. The information underlying the maps is provided in the appendix. Fig. 1 summarizes the state-level evidence for the model with a break, as summarized by the log Bayes factors. The model with a break is preferred for all but the District of Columbia and six states—Georgia, Maine, Maryland, New York, South Carolina, and West Virginia—all states located on or near the Atlantic coast. For 38 states, the log Bayes Factor is greater than 2.3, meaning there is strong evidence for a structural break using the Jeffreys scale. The additional exceptions to the states listed above are Massachusetts, Nebraska, Tennessee, and Vermont.

Some of the states for which there is strong evidence of a break experience their volatility reduction outside three years of the estimated aggregate break date. Fig. 1 also separates from the rest those states which exhibit strong evidence of a break outside of

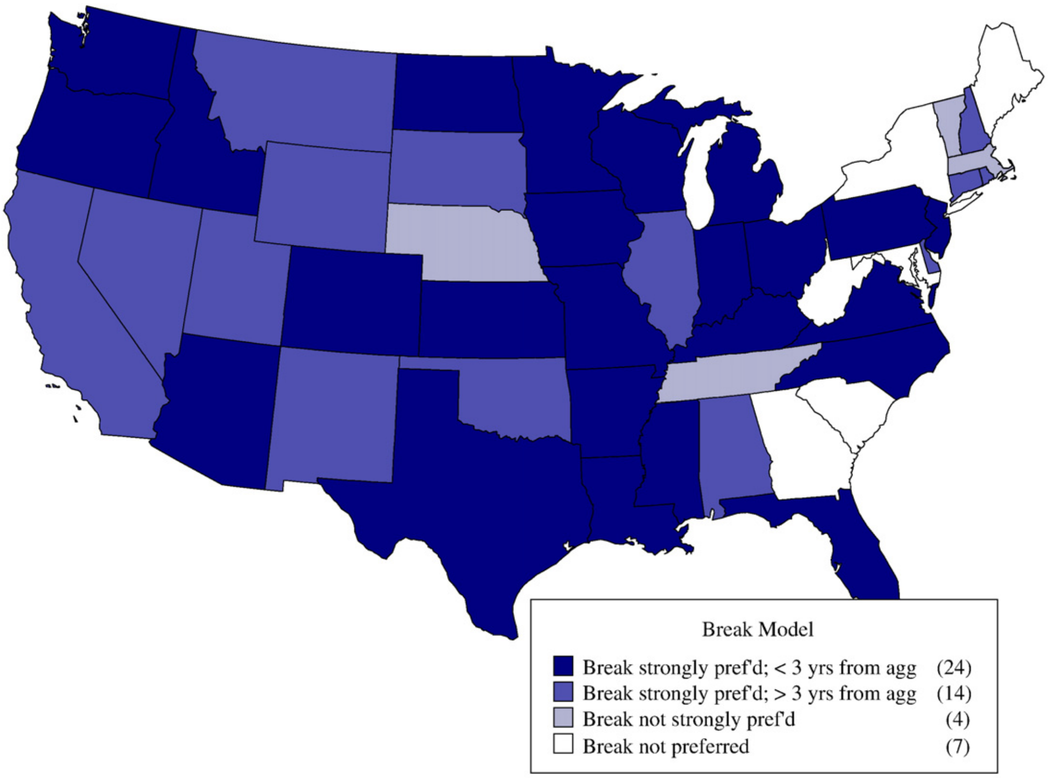

Fig. 1. Evidence for model with break.

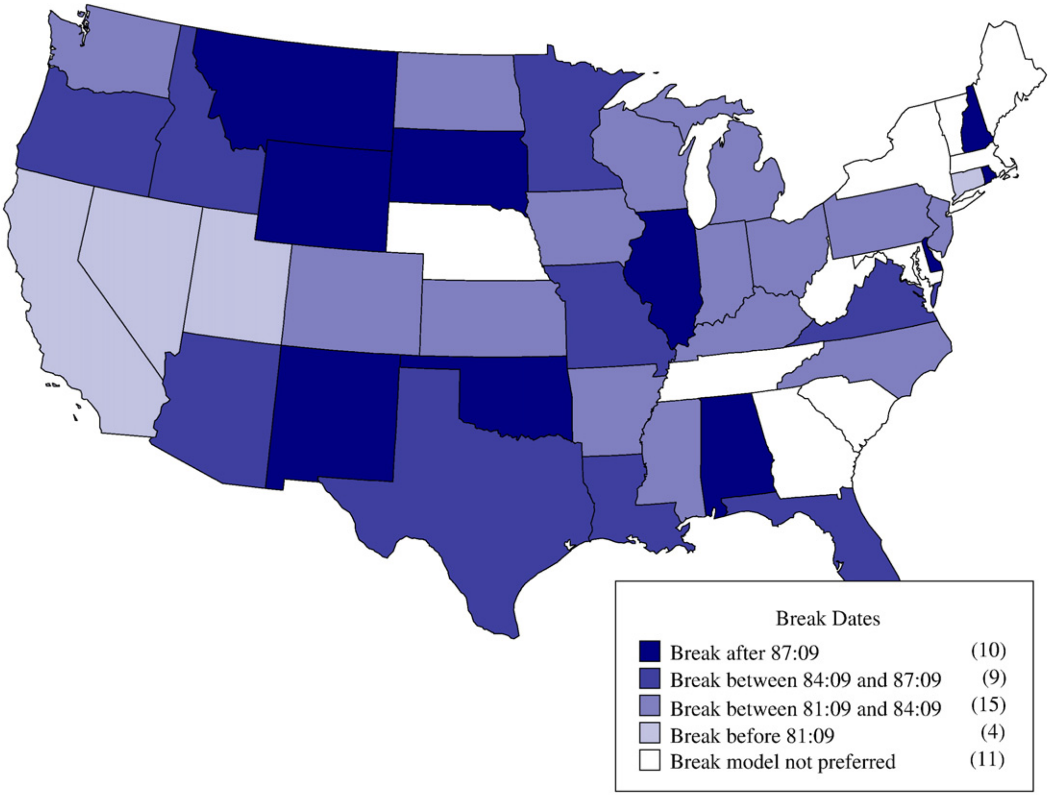

Fig. 2. Break timing across states.

three years of the median date for the aggregate—14 of the states.[6] Finally, for 27 states, the 90 percent posterior error band around the median break date does not overlap with that for the aggregate.[7]

Fig. 2 gives the posterior median of each state's break date, with lighter colors indicating an earlier break. These results highlight the substantial heterogeneity in the timing of each state's volatility reduction, which appears to be influenced by geographic contiguity. Specifically, the figure suggests some geographical pattern to the break dates, with three states in the West experiencing the volatility reduction first, followed by the Great Lakes and Plains. Moreover, some states do not experience a decline in volatility, with these states mostly located in the East.

Fig. 3 illustrates the posterior median of the ratio of the unconditional standard deviation of y_{it} in the pre- and post-break periods.[8,9] Darker-colored states have a lower volatility ratio, indicating a higher reduction in variance. Only the District of Columbia has a ratio greater than one, meaning that volatility actually increased after the break. Recall, however, that D.C. is one case for which the model with no structural break was the preferred model. For the other states, the largest volatility reduction occurred in Arkansas, for which the posterior median of the volatility ratio is 0.47, while the smallest occurred in South Carolina, for which the posterior median of the ratio is 0.87. Again, South Carolina is a state for which the preferred model does not have structural break. For 20 of the states, the volatility ratio is smaller than for the aggregate data, meaning the volatility reduction is larger.

From these results we can rule out that the volatility reduction in aggregate employment arose from state business cycles becoming less synchronous while state-level volatility remained the same.[10] Our results above indicate clearly that states experienced volatility reductions of their own. Further, an examination of the concordance of state business cycles shows that state economies actually became *more* synchronous after September 1984, the date of the break in the national employment series. Specifically, we calculated the concordance between the business cycles of each state and every other state and found the average

[6] Results for the posterior 5th and 95th percentiles for the break date are in the appendix.

[7] See the appendix for the identities of these states. This preponderance of state breaks that are not coincident with the aggregate break is in contrast with Anderson and Vahid (2003), who find only two break dates in state-level personal income that are statistically different from the aggregate break date.

[8] Fig. 3 illustrates the ratio of volatilities regardless of whether or not the break is preferred.

[9] In addition, we note that many state-level business cycles became more persistent, i.e., both transition probabilities p and q rose after the break.

[10] We are indebted to one of the referees for pointing this out to us.

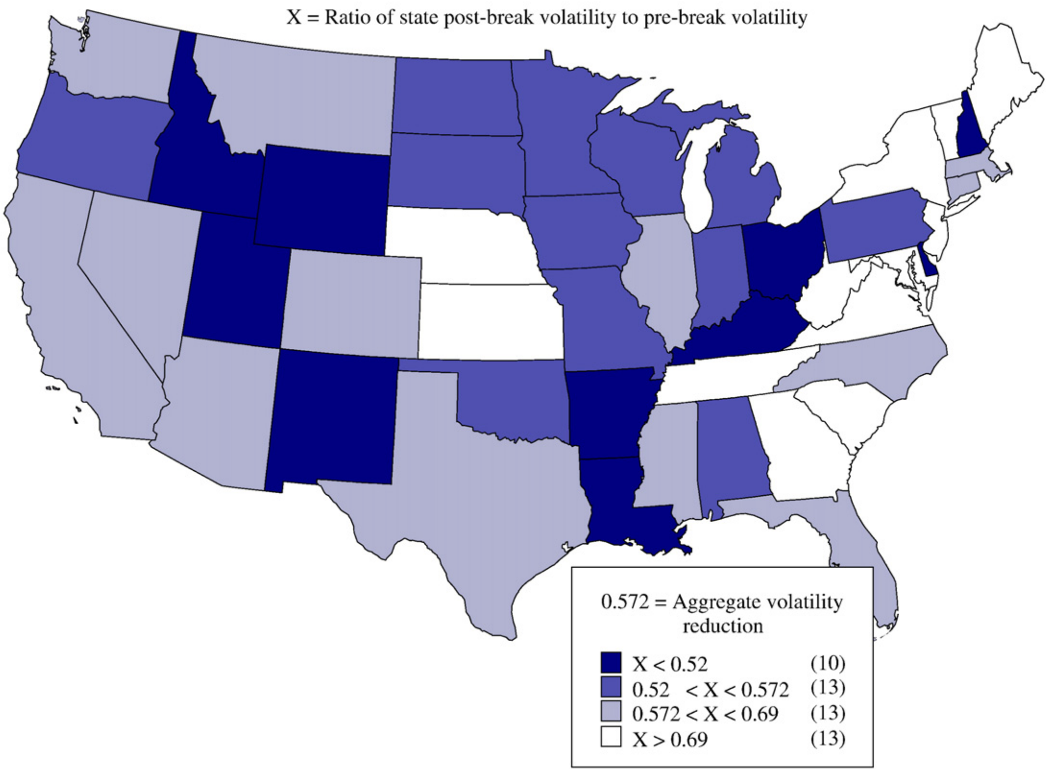

Fig. 3. Magnitude of volatility reduction.

concordance before the aggregate break to have been 0.57, while the post-break average concordance was 0.81.[11] The complete set of state average concordances for the two periods is provided in an appendix.

4. Explaining states' Great Moderations

In the previous section, we documented state-level heterogeneity in the timing and magnitude of the volatility reduction in total payroll employment. Here, we check whether the volatility ratios (Fig. 3) and the break dates (Fig. 2) are related statistically to state-level characteristics. To obtain our list of possible covariates, we use as a guide the five hypotheses posited by the literature on the origins of the Great Moderation, which we summarize below. In addition to helping explain our state-level differences, this exercise should shed some light on the plausibility of the five hypotheses.

4.1. Hypotheses for the Great Moderation

According to the *inventory hypothesis*, innovations in inventory management in the durable-goods sectors have led to reductions in the volatility of output (Kahn et al., 2002).[12] If this hypothesis holds, we should see a negative relationship between the volatility ratio and the durable-goods share, but that there should be no such link between the volatility ratio and other sectors of the economy. To account for the rest of the economy we include the nondurable-goods share and the initial (pre-break) average volatility.

According to the *good-luck hypothesis*, the reduction in output volatility was associated with reductions in the volatility of various (and often unspecified) innovations and shocks (Ahmed et al., 2004). These shocks and innovations can come from a myriad of sources, two of which we control for in our regressions: energy shocks and productivity shocks. If reductions in the volatility of energy prices have led to reductions in output volatility, we might expect to find that the volatility ratio is negatively related to the extractive-industries employment share. Also, because reductions in the volatility of energy prices should affect the users of energy, we might expect that the reductions in the volatility of employment were greatest in the states with the highest energy-usage rates. If the good luck was instead through reductions in the volatility of productivity shocks throughout the economy, we should find that the volatility ratio is negatively related to the relative importance of both durable and nondurable goods.

[11] The concordance of two business cycles is the percentage of time that the two economies are in the same regime (Harding and Pagan, 2002), which we calculate using the probabilities of the regimes.

[12] For alternative perspectives on the role of inventory management, see Herrera and Pesavento (2005), Ramey and Vine (2004), and Khan and Thomas (2007).

Boivin and Giannoni (2006) posit that it was reductions in the volatility of monetary policy that led to reductions in output volatility. According to this hypothesis, the Fed has changed the way in which it reacts to inflation and output tradeoffs, meaning that it has become less willing to try to fine tune the output side of the economy by adjusting monetary policy, thereby reducing output volatility. If this *monetary hypothesis* is correct, we should see statistical relationships between the sizes and timing of volatility reductions and measures of the three channels of monetary policy: the money channel, the broad credit channel, and the narrow credit channel. Detailed discussions of these channels are provided by Cecchetti (1995), Bernanke and Blinder (1988), and Kashyap and Stein (1995, 2000), respectively.

Carlino and DeFina (1998) employ a set of state-level characteristics to capture the importance of each of these channels: Through the money (or direct) channel, because durable-goods industries are relatively interest-rate sensitive, the largest volatility reductions should be in states with large durable-goods sectors, i.e., the volatility ratio and the durable-goods share should be negatively related. Through the broad credit channel, because large firms are thought to have information and transaction-cost advantages in dealing with banks, large firms are less affected by volatile monetary policy. In other words, the relationship between the volatility ratio and average firm size should be positive. Through the narrow credit channel, because large banks have more alternative funding sources when monetary policy is tight, states in which large banks are relatively more important should be less affected by volatile monetary policy; i.e., there should be a positive relationship between the volatility ratio and the banking concentration.

Jaimovich and Siu (in press) argue that *changing demographics*, in particular a smaller share of the relatively volatile 15–29 year old group, meant that the economy as a whole became less volatile. Thus, states that saw larger reductions in this age group should also have seen greater reductions in volatility. By the same token, larger changes in the shares of other volatile groups should also translate into larger volatility reductions. In particular, the significant increases that occurred in the 1970s in the shares of those with at least a high school diploma might be related to the Great Moderation.

Most recently, Dynan et al.(2006) suggest that *banking deregulation*, specifically the relaxation of Regulation Q, can explain the Great Moderation. We look more broadly at the deregulation that occurred in the banking sector since the 1970s. Of particular interest for us since we are viewing events at the state level is the wave of merger and branching deregulation that states enacted. Unlike the phase-out of Regulation Q, which occurred through the first half of the 1980s, merger and branching deregulation occurred at different times across states, and might be consistent with the sizes and patterns of breaks that we have reported. Strahan (2003) provides a discussion of this deregulation, which allowed interstate branching versus mergers and acquisition, unrestricted intrastate branching, and interstate banking.

4.2. Covariates for volatility ratios

To capture the effects of the first three hypotheses, we include as independent variables the nondurable and durable employment shares, the extractive-industries employment share, per capita energy consumption, average firm size, and the deposit share at the five largest banks. To capture the effect of banking deregulation, we include dummy variables to indicate whether the three types of deregulation were in place at the time of the break. Finally, we capture the effects of demographic changes by including the changes in the shares of states' populations with high school diplomas and the changes in the shares aged 15–29. Table 2 outlines the directions of the relationships between these variables and the volatility ratios and the break dates that fit the various hypotheses of the Great Moderation. The data sources and summary statistics for all of these variables are provided in an appendix.

We estimate the relationship between the volatility ratio and these variables with a spatial error model that uses a contiguity matrix for spatial weights. As shown in Table 3, despite the fact that the coefficient on the spatial error is not statistically significant, the results are stronger than when we use OLS. Our results are consistent with several of the hypotheses and inconsistent with two of them. First, there is a negative and statistically significant relationship between the volatility ratio and the durable-goods share, but not the nondurable-goods share: the larger a state's durable-goods sector was, the larger was the reduction in volatility. This result is consistent with the inventory hypothesis, the productivity version of the good-luck hypothesis, and the money channel of the monetary hypothesis.

Note that volatility reductions tended to be larger in states with high pre-break volatilities, indicating that the volatility reductions were not coming solely through the durable-goods sector, but were based more broadly, even after controlling for durable-goods

Table 2
Expected covariations corresponding to the hypotheses for the Great Moderation

	Inventory	Good luck		Monetary channels			Demography	Deregulation
		Oil	Prod'ty	Money	Broad	Narrow		
Initial volatility	0							
Durable-goods share	–		–	–				
Nondurable-goods share	0		–					
Extractive share		–						
Energy consumption		–						
Firm size					+			
Deposit share of 5 largest banks						+		
Banking deregulation dummies								–
Increase in share w/HS diploma							–	
Decrease in share aged 15–29							–	

Table 3
Volatility reduction and state characteristics

	Spatial Error Model			Ordinary Least Squares		
	Coefficient	s.e.	*t*-stat	Coefficient	s.e.	*t*-stat
Pre-break standard deviation	−0.425	0.091	−4.68	−0.414	0.108	−3.83
Average durable-goods share	−0.780	0.260	−3.00	−0.822	0.318	−2.59
Average nondurable-goods share	−0.295	0.536	−0.55	−0.343	0.617	−0.56
Average extractive share	1.171	1.109	1.06	0.978	1.319	0.74
Average per capita energy consumption	−0.341	0.137	−2.49	−0.289	0.146	−1.98
Average firm size	0.015	0.007	1.89	0.013	0.008	1.68
Deposit share of 5 largest banks	−0.023	0.091	−0.25	−0.008	0.109	−0.08
Intrastate branching via M&A prior to break	−0.017	0.036	−0.46	−0.009	0.042	−0.22
Unrestricted intrastate branching prior to break	0.095	0.041	2.29	0.088	0.050	1.74
Interstate banking prior to break	−0.009	0.038	−0.23	−0.006	0.045	−0.13
Increase in share w/HS diploma	0.911	0.421	2.16	0.812	0.495	1.64
Decrease in share aged 15–29	1.480	1.528	0.97	0.876	1.839	0.48
Constant	0.644	0.163	3.96	0.604	0.190	3.17
λ	−0.018	0.015	−1.21	–	–	–
Wald test of λ=0	$\chi^2(1)$=1.464			–		

Dependent variable=post-break volatility/pre-break volatility.
The spatial error model estimated by maximum likelihood with spatial weights that are binary to indicate contiguity. Both models include Huber/White/Sandwich robust standard errors.

shares. This result suggests that whatever led to reductions in the volatility of output, it was not confined to the durable-goods sector, thereby weakening the evidence in favor of the inventory hypothesis. Further, the case for the monetary hypothesis is strengthened by the positive link between the volatility ratio and average firm size, suggesting a role for the broad monetary channel. Also, evidence in favor of the oil version of the good-luck hypothesis is provided by the negative link between the volatility ratio and per capita energy consumption: states with higher average energy consumption tended to see larger reductions in volatility.

Our results so far do not provide enough evidence to choose from among the inventory, good-luck, or monetary hypotheses. On the other hand, the results are stronger in terms of ruling out the demography and bank deregulation hypotheses. Specifically, the positive sign on the dummy for unrestricted intrastate branching indicates that states that had done this deregulation before their break tended to see smaller volatility reductions. Similarly, the positive sign on the change in the share with a high school diploma runs counter to expectations about the effects of demographics: The larger was a state's increase in its share in this less volatile group, the smaller was its volatility reduction.

4.3. Break probabilities

As mentioned above, our cross-section of volatility reductions is broadly consistent with parts of each of the three main hypotheses for the Great Moderation. This is not completely satisfying in that we are left with little to distinguish among the three hypotheses and are left without any evidence from the time dimension of the Great Moderation. To address both of these issues, we make use of the time information that is available to us—the dates of the states' structural breaks. We use these dates and estimate a proportional hazards model to see if any from our list of state characteristics are associated with the timing of state reductions in volatility.[13] If, for example, the inventory hypothesis holds, then states that produced relatively more durable goods should have been more likely experience a volatility reduction before other states. A positive coefficient on a variable would indicate that a higher value for the variable is associated with a higher chance of the break occurring sooner.

From the list of variables used above, we excluded the banking deregulation dummies because they seem to be unlikely candidates for causing the breaks. We address the banking deregulation hypothesis in a separate subsection below. As reported in Table 4, the coefficient on the durable-goods share is statistically no different from zero, indicating that we cannot say that the timing of states' structural breaks were related to the sizes of their durable-goods sectors. A statistically significant positive sign on this coefficient would have been consistent with the inventory hypothesis, the productivity version of the good-luck hypothesis, and the monetary hypothesis.

The coefficient on the nondurable-goods share is negative and statistically significant, indicating that a larger nondurable-goods share meant a later break. This result is counter to the productivity version of the good-luck hypothesis, by which productivity increases throughout the economy led to reduced volatility. The oil version of the good-luck hypothesis is also inconsistent with our results because the significant negative coefficient on per capita energy consumption indicates that higher

[13] The proportional hazards model is a tool common in survival analysis that models the effect of covariates (often termed 'treatments') on the time before an event, e.g., death, mechanical failure, or, in our case, structural change. The proportional hazards model assesses the covariate's effect on the probability of structural change in any given period and is consistent with our underlying assumption of a single break in volatility. In the alternative case of multiple fluctuations between high and low volatility phases, the binomial probit or logit models might be more appropriate.

Table 4
Proportional Hazards Model

	Coefficient	s.e.	*t*-stat
Average durable-goods share	−5.29	4.36	−1.21
Average nondurable-goods share	−23.18	7.64	−3.03
Average extractive share	1.96	1.92	1.02
Average per capita energy consumption	−42.45	18.02	−2.36
Average firm size	0.15	0.07	2.12
Deposit share of 5 largest banks	−0.97	1.11	−0.88
Average share w/4 or more yrs. of HS	−3.46	3.30	−1.05
Average share aged 15–29	23.38	11.38	2.05
Constant	−70.15	9.23	−7.60

Dependent variable = break month (1956:01 = 0).
Hazards model with Huber/White/Sandwich robust standard errors.

energy consumption meant a later volatility reduction. Finally, the share aged 15–29 (a relatively volatile group) tends to mean an earlier, counter to the predictions of the age version of the demography hypothesis.

Of the five hypotheses, only the monetary hypothesis is consistent with the results from our hazards model. Specifically, consistent with the broad channel for monetary policy, states with relatively high shares of large firms tended to have had later volatility reductions. On the other hand, none of the coefficients on the variables representing the money and narrow channels of monetary policy are statistically different from zero.

4.4. The banking deregulation and break dates

At the national level, the relaxation of Regulation Q seems to coincide with the timing of the aggregate volatility reduction, lending support to contentions of Dynan et al. (2006). Given timing of the state-level volatility reductions, however, we can rule out the relaxation of Regulation Q as a cause of the Great Moderation. Regulation Q was phased out over a number of years in the early 1980s, so it is difficult to square with the fact that a large number of states experienced their breaks in advance of this deregulation.

Confidence in the banking deregulation hypothesis is eroded further by an examination of the timing of state-level banking deregulations relative to states' volatility reduction. In lieu of a formal analysis, we offer Fig. 4, which plots the difference in the timing of the earliest banking regulation change and each state's volatility reduction on the horizontal axis and the size of the state's volatility reduction on the vertical axis. A zero on the horizontal axis indicates that a state's break date and its banking deregulation were coincident. While a number of states did have deregulation prior to their volatility break, a substantial proportion experience their volatility reductions two to four years before any change in banking regulations. Large states are split. In particular, California, Illinois, and Ohio deregulated before their volatility breaks while Indiana, Michigan,

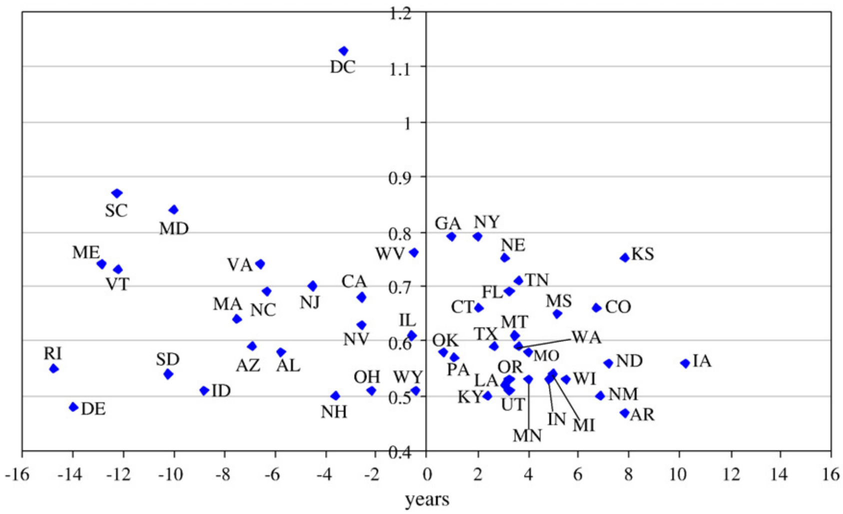

Fig. 4. Volatility reductions and banking deregulation. The vertical axis is the volatility ratio while the horizontal axis is the difference between the date of the state's earliest banking deregulation and the estimated date of its structural break.

Table 5
Consistency of results with the hypotheses for the great moderation

	Inventory	Good luck		Monetary channels			Demography	Deregulation
		Oil	Productivity	Money	Broad	Narrow		
Initial volatility	I							
Durable-goods share	C, N		C, N	C, N				
Nondurable-goods share	C, N		N, I					
Extractive share		N, N						
Energy consumption		C, I						
Firm size					C, C			
Deposit share of 5 largest banks						N, N		
Banking deregulation dummies								I, I
Increase in share w/HS diploma							I, N	
Decrease in share aged 15–29							N, I	

The first letter refers to the volatility ratio while the second letter (if there is one) refers to the break date. The letter “C” indicates “consistent with the hypothesis” (statistically significant and with the right sign) an “I” indicates “inconsistent with the hypothesis” (statistically significant and with the wrong sign) and an “N” indicates that it is neither consistent nor inconsistent with the hypothesis (not statistically significant).

New York, Pennsylvania, and Texas experienced their volatility reductions after their change in banking regulations. This suggests that changes in banking regulation, at least at the state level, could not have been the catalyst for state-level volatility reductions.

4.5. The plausibility of the five hypotheses

Taken together, we can assess the overall plausibility of the five hypotheses for the Great Moderation according to whether or not our results from Tables 3 and 4 are consistent with the expected results for the hypotheses. In Table 5, an estimated coefficient is called: “consistent” with a hypothesis if it is statistically significant and has the expected sign; “inconsistent” with a hypothesis if it is statistically significant and the sign is opposite of what was expected; and “neither” if it was statistically no different from zero. A plausible hypothesis is one for which none of the estimated coefficients were inconsistent. Overall, of the five hypotheses, the monetary hypothesis remains plausible.

The inventory hypothesis is implausible because, although states with large durable-goods sectors saw larger volatility reductions, large reductions were also experienced by states with high pre-break volatility levels unrelated to durable goods. The negative relationships between the probability of a break and per capita energy consumption and nondurable-goods share suggest that neither version of the good-luck hypothesis is plausible. The demography hypothesis is implausible also because smaller volatility reductions tended to occur in states that saw small changes in the share with a high school diploma, and the size of the 15–29 age group tended to mean a higher break probability.

The banking deregulation hypothesis is implausible on three fronts. First, the relaxation of Regulation Q occurred well after the volatility reductions of a large number of states; Second, states that deregulated their banking sector prior to their break tended to see smaller volatility reductions; And, third, a substantial proportion of states experienced their volatility reductions well in advance of any change in their banking regulations.

According to our results, only the monetary hypothesis remains a plausible explanation for the Great Moderation. The hypothesis is consistent with our findings that states with large durable-goods sectors tended to have experienced larger reductions in volatility, and a high average firm size tended to mean a smaller volatility reduction and a higher probability of a structural break.

5. Summary and conclusions

This paper documented the Great Moderation at the state level and found significant heterogeneity in the timing and magnitude of states' structural breaks. Specifically, we found that 38 states experienced a structural break and that 14 states had breaks that occurred at least three years before or after the aggregate break, which we place at September 1984. The states for which we found weak or little evidence of a break tended to be along the Atlantic coast.

Typically, when macroeconomists are looking for explanations for the Great Moderation, they have only the single aggregate occurrence with which to work. As a result, several hypotheses have gained support on the basis of temporal coincidence between various events or trends and this single volatility reduction. Unfortunately for this approach, however, a surfeit of events occurred alongside the Great Moderation, so it is difficult to sort out the many theoretically plausible explanations. Our set of state-level great moderations might, therefore, be useful in sorting through the various hypotheses.

Of the five main hypotheses that have been put forth, our results suggest that four of them—the inventory, good-luck, banking deregulation, and demography hypotheses—are implausible because they are statistically inconsistent with the state-level pattern of structural breaks. On the other hand, we found that the monetary hypothesis remains a plausible explanation of the Great Moderation in that it is not inconsistent with the state-level experience.

Appendix: Estimation results underlying Figs. 1–3

	Log Bayes factor	Volatility ratio	Break Date		5th and 95th percentiles			Log Bayes factor	Volatility ratio	Break date		5th and 95th percentiles	
United States	20.9	0.57	September	1984	−6	8							
Alabama*	20.5	0.58	January	1987	−8	10	*Nebraska*	*1.4*	*0.75*	*March*	*1982*	*−76*	*26*
Arizona*	21.4	0.59	March	1982	−14	6	Nevada*	31.2	0.63	November	1977	−14	38
Arkansas*	54.6	0.47	June	1981	0	4	New Hampshire*	27.2	0.50	November	1990	−21	10
California*	28.3	0.68	November	1977	−14	49	New Jersey*	11.8	0.70	October	1981	−72	28
Colorado*	26.8	0.66	August	1981	−68	10	New Mexico*	9.9	0.50	June	1982	−35	5
Connecticut	21.0	0.66	March	1978	−28	90	*New York*	*−7.7*	*0.79*	*April*	*1974*	*−22*	*169*
Delaware*	455.8	0.48	April	1989	−3	11	North Carolina*	8.4	0.69	August	1981	−61	13
Dist. of Col.	*−10.4*	*1.13*	*July*	*1978*	*−146*	*36*	North Dakota*	30.8	0.56	February	1980	−37	10
Florida*	18.4	0.69	January	1982	−47	8	Ohio*	36.9	0.51	June	1981	−5	9
Georgia	*−2.0*	*0.79*	*April*	*1982*	*−89*	*13*	Oklahoma*	18.0	0.58	August	1986	−6	13
Idaho	32.3	0.51	February	1984	−8	12	Oregon*	37.0	0.53	January	1982	−8	10
Illinois	11.7	0.61	November	1986	−18	14	Pennsylvania*	18.4	0.57	March	1981	−10	8
Indiana*	37.2	0.53	June	1981	−5	6	Rhode Island*	16.4	0.55	January	1990	−5	10
Iowa*	28.6	0.56	January	1981	−10	7	*South Carolina*	*−3.0*	*0.87*	*July*	*1987*	*−22*	*15*
Kansas	3.6	0.75	June	1979	−36	123	South Dakota	29.2	0.54	July	1985	−2	4
Kentucky*	42.8	0.50	November	1981	−6	9	*Tennessee*	*1.5*	*0.71*	*August*	*1981*	*−7*	*57*
Louisiana	35.5	0.52	March	1984	−4	7	Texas	20.4	0.59	August	1984	−3	10
Maine	*−2.2*	*0.74*	*February*	*1988*	*−23*	*15*	Utah*	63.3	0.51	January	1978	−27	12
Maryland	*−9.2*	*0.84*	*April*	*1985*	*−41*	*29*	*Vermont*	*0.9*	*0.73*	*June*	*1987*	*−27*	*41*
Massachusetts	*2.2*	*0.64*	*October*	*1990*	*−27*	*8*	Virginia	4.5	0.74	November	1984	−13	16
Michigan*	33.3	0.54	April	1981	−15	21	Washington	22	0.59	August	1981	−6	77
Minnesota*	35.2	0.53	April	1982	−8	4	*West Virginia*	*−18.9*	*0.76*	*October*	*1987*	*−14*	*49*
Mississippi*	17.2	0.65	February	1981	−27	7	Wisconsin*	32.4	0.53	October	1981	−7	15
Missouri*	22.5	0.58	April	1982	−3	14	Wyoming	33.4	0.51	September	1987	−28	9
Montana	19.0	0.61	October	1986	−101	21							

States in italics are those for which the model with a break is not at least “strongly preferred.” The 5th and 95th percentiles of the posterior distribution are expressed as differences in months from the posterior median. An “*” indicates that the 90% posterior error band around the median break date does not overlap with that for the aggregate.

Appendix: Summary statistics

	Mean	Standard deviation
Volatility ratio	0.628	0.126
Pre-break standard deviation	0.473	0.112
Average durable-goods share 1969–83	0.099	0.051
Average nondurable-goods share 1969–83	0.076	0.042
Average extractive share 1969–83	0.014	0.021
Average per capita energy consumption 1969–83	0.354	0.119
Average firm size 1988	16.333	3.044
Deposit share of 5 largest banks 1983	0.540	0.218
Increase in share w/HS diploma	0.211	0.042
Decrease in share aged 15–29	0.013	0.011

Industry shares are from the BLS; per capita energy consumption is from the Energy Information Administration; average firm size is from Statistics of U.S. Business; the deposit share of the five largest banks is from the State and Metro Area Data Book 1986. Average firm size and deposit share are for the first year for which data are available. The increase in the share of those 25 or older with a high school diploma is the difference between the average for 1990 and 2000 and the average for 1970 and 1980. The decrease in the share aged 15–29 is the difference between five years before the break and five years after it.

Appendix: Pre- and post-break average concordances

	Pre-break	Post-break		Pre-break	Post-break
Alabama	0.64	0.84	Nebraska	0.43	0.84
Arizona	0.63	0.83	Nevada	0.46	0.84
Arkansas	0.61	0.83	New Hampshire	0.53	0.84
California	0.61	0.82	New Jersey	0.58	0.85

(*continued on next page*)

Appendix (*continued*)

	Pre-break	Post-break		Pre-break	Post-break
Colorado	0.60	0.83	New Mexico	0.62	0.85
Connecticut	0.57	0.83	New York	0.64	0.85
Delaware	0.61	0.83	North Carolina	0.66	0.84
Dist. of Col.	0.61	0.82	North Dakota	0.66	0.85
Florida	0.62	0.82	Ohio	0.66	0.83
Georgia	0.63	0.82	Oklahoma	0.64	0.83
Idaho	0.63	0.82	Oregon	0.65	0.85
Illinois	0.62	0.82	Pennsylvania	0.65	0.84
Indiana	0.62	0.82	Rhode Island	0.66	0.84
Iowa	0.60	0.82	South Carolina	0.66	0.83
Kansas	0.55	0.82	South Dakota	0.65	0.84
Kentucky	0.52	0.81	Tennessee	0.64	0.84
Louisiana	0.51	0.82	Texas	0.63	0.83
Maine	0.53	0.82	Utah	0.60	0.83
Maryland	0.52	0.82	Vermont	0.60	0.83
Massachusetts	0.49	0.81	Virginia	0.62	0.83
Michigan	0.47	0.83	Washington	0.63	0.82
Minnesota	0.46	0.83	West Virginia	0.64	0.83
Mississippi	0.45	0.83	Wisconsin	0.62	0.83
Missouri	0.43	0.84	Wyoming	0.61	0.83
Montana	0.42	0.84	*Mean*	*0.57*	*0.81*

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