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Countercyclical Policy and the Speed of Recovery After Recessions*

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Abstract

We consider the effect of some policies intended to shorten recessions and accelerate recoveries. Our innovation is to analyze the duration of the recoveries of various U.S. states, which gives us a cross-section of both state- and national-level policies. Because we study multiple recessions for the same state and multiple states for the same recession, we can control for differences in the economic conditions preceding recessions and the causes of the recessions when evaluating various policies. We find that expansionary monetary policy at the national level helps to stimulate the exit of individual states from recession. We find that exogenous measures of decreases in taxes or targeted increases in federal spending reduce recovery times for state-recessions. We also find ambient economic conditions can extend expected recovery times: other states in the same region suffering from recession around the same time, the length of the preceding recession, and increases in oil prices.

[JEL codes: C23, E32]

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1 Introduction

The U.S. business cycle is often characterized as an aggregate phenomenon that moves the economy between recessionary and expansionary phases [e.g., Burns and Mitchell (1946); Hamilton (1989); and many others]. Because most empirical papers assume a binary process for the business cycle, few consider how the economy recovers from recession. Models that include only expansion and recession regimes have so-called L-shaped recoveries that never return to the original trend and may be ill-equipped for modeling recoveries, especially for variables such as employment.[1] For example, nonlinear models, such as the popular Markov-switching model, assume that the depth of recessions, the trajectory away from the troughs, and lengths of the subsequent recovery periods are the same for all recessions.

These models also make evaluation of countercyclical policy difficult. Linear models assume a proportional response to policy; Markov-switching models are simply piecewise linear. Moreover, because there are relatively few recession experiences (11 in the post-War period), determining how a recovering economy responds to policy is problematic. Some have opted to study disaggregate data to explain aggregate labor market conditions. For example, Jaimovich and Siu (2012) examine the effect of recent recoveries on different occupations and demonstrate that jobless recoveries are intrinsically linked to another phenomenon: job polarization, in which middle-skilled routine jobs disappear during recessions.

We approach the problem from the perspective of the policymaker: Are there policies—either national or state-level—that affect the duration of economic recoveries—specifically, recoveries of state-level employment after recessions? We consider three policies that have traditionally been viewed as useful for combating recessions: (1) monetary policy, (2) fiscal policy (increased government spending and decreased taxes), and (3) the use of state "rainy day" funds.

Because of the relative dearth of national-level recessions, we exploit the heterogeneity in the states' recession experiences over time and across space. According to Owyang, Piger, and Wall (2005) and Hamilton and Owyang (2012), some states and regions within the U.S. may deviate from the pattern of the national business cycle. Carlino and Sill (2001) also find large differences

[1] Notable exceptions are Kim, Morley, and Piger (2005, KMP), who model a deterministic post-recession bounce-back phase, and Dueker (2006), who models the economy as a four-regime Markov process, which includes a high-growth recovery regime and a slow-growth regime. In these models, the duration of the recovery period is either deterministic (KMP) or probabilistic (Dueker) but never an explicit function of policy or regulation.

in business cycle volatility across regions. They find that each region has a different mixture of industries, experiences different shocks to its output, and thus experiences region-specific business cycles. Because of the heterogeneity across states, enacting expansionary policy during a national recession may stimulate some regional labor markets more than others.

These papers also argue that the similarity in states' business cycles can be associated with similarities in certain state-level characteristics. For example, Owyang, Piger, and Wall (2005) and Hamilton and Owyang (2012) argue that the similarity in states' business cycles can be associated with similarities in certain state-level characteristics— e.g., the fraction of employment in the manufacturing sector or the percentage of state personal income obtained from the energy sector. Others have surmised that the dispersion in unemployment rates across Europe is caused by centralized collective bargaining and government policies that hinder regional labor market adjustments [e.g., Blanchard and Portugal (2001)]. In order to identify the effect of policy, we need to control for variation in the economic conditions and demographics across states that may magnify any heterogeneous effects. Therefore, potential characteristics affecting recovery duration could be inherent to the state (e.g., manufacturing share of employment) or be specific to the particular recession experience (e.g., the depth of the recession, the number of other states affected by the recession) and must be controlled for when evaluating the efficacy of policies.

We also take a different approach than the extant literature using Markov-switching models by explicitly considering the duration of the recovery period as a function of time-specific, state-specific, and state-time-specific covariates. The novelty of our approach is that we allow the policy effects to depend (nonlinearly) on the depth of the recession, the size of the policy shock, etc. Moreover, because we do not fix the depth of the recession ex ante (as does the Markov-switching model), we can exploit the heterogeneity across the recession experiences. We consider all state-level recession experiences individually, regardless of whether they appear state-specific or associated with a national recession. Our identification of the effects of policy comes through the variation in the magnitudes and timing of the state-level recessions. We model the effect of a variety of covariates on the duration of the recovery as an accelerated failure time model, where the identified treatment increases or decreases the length of the recovery multiplicatively. Because the number of covariates can be large, we utilize a Bayesian algorithm that reduces the dimension of the covariate vector by excluding variables that have no effect on the duration of recoveries.

We find that expansionary monetary policy at the national level helps to stimulate individual states' recoveries from recession and we quantify the extent to which monetary policy accelerates recoveries. We find that exogenous measures of decreases in taxes [e.g., as in Romer and Romer (2010)] or targeted increases in spending [e.g., location-specific military spending as in Nakamura and Steinsson (2014)] appear to decrease recovery times. Our results also suggest that expected recovery times are longer if other states in the same region are suffering from recession around the same time, if the preceding recession is longer, or if we see significant shocks to oil prices at the peak.

The balance of the paper is organized as follows: Section 2 reviews the data and describes our characterization of recessions and recoveries at the state level. Section 3 outlines the empirical model and describes the methods used for estimation. Section 4 presents the results of the estimation. We briefly describe the differential effects of state-level heterogeneity and variation in the depth and length of the recessions. We then present the main results on the effects of policy. Section 5 presents some alternative models to verify the robustness of our baseline model. Section 6 offers some conclusions.

2 Data

The model below is estimated using the duration of recoveries, policy variables, and state-level characteristics that result in the heterogeneous response to expansionary policy. Here, we describe the construction of the data. Because states may vary in the timing and frequency of their recessions as in Owyang, Piger, and Wall (2005), we must first define recessions and then define recoveries. We then discuss the state- and national-level characteristics that might affect the duration of recoveries. Finally, we outline the data used to measure various countercyclical policies.

2.1 Defining Recessions and Recoveries

Our primary business cycle indicator is the seasonally-adjusted monthly level of payroll employment for the 48 contiguous states beginning in 1939 for all states except Illinois (1947), Michigan (1956), and Minnesota (1950).[2] We treat each state-recession experience on a case-by-case basis, so that

[2] Employment has the tendency to lead peaks and lag troughs, particularly in the past few national recessions. While employment might not be the optimal business cycle indicator, we use it because the longer sample provides

panel need not be balanced. Because the state-level data can be noisy, we define a state in recession when employment falls for at least six of eight consecutive months—roughly speaking, at least two consecutive quarters. The peak is the month immediately preceding the recession and the trough is the final month of the recession. The length of the recession counts the months between peak and trough and the recovery period counts the months after the trough required to reach the pre-recession level of employment.[3]

Table 1 shows characteristics of business cycles for the states and the nation, where the national recessions are defined by the NBER. The table provides the number of recessions experienced over the sample period for each state; the average number of months in that state's recessions; the mean and standard deviation of the recovery times following each recession; and the average depth of each state's recessions taken as the employment loss over the recession as a percentage of the average size of the labor force over the years 1990-2006. New York and Rhode Island experienced the most recessions (15) between 1939 and 2012, three more than the nation experienced during the same period. North Dakota is the fastest-recovering state, with an average recovery time of 4.8 months—almost half that of Alabama (8.6 months), the next-fastest-recovering state.

While most states have similar business cycles as the nation, heterogeneity in the timing of the recessions still remain [Owyang, Piger, and Wall (2005)]. To demonstrate the differences between the state recession experiences and the nation, we compute the concordance between state-recession periods and the NBER recession dates. Concordance measures the percentage of months that the state and the national series are both in recession or both out of recession. The average concordance between state-recessions identified with payroll employment data and the NBER recession dates, across all states, is 0.862. The concordance values for all state pairs range between 0.759 and 0.935, thus suggesting a fair amount of variation between the timing of state-level recessions and aggregate recessions identified for the U.S. as a whole.

We find heterogeneity between the recession and recovery experiences of states that is not evident in a comparison of national recessions. While the lengths of the national recessions remain relatively constant, employment recoveries are much slower from the last three recessions (33

us with a large number of recessions, which we need for our analysis.

[3] Another approach would be to use statistical methods like those in Owyang, Piger, and Wall (2005). Hamilton (2011), however, shows that simple heuristic rules for defining recessions approximates more rigorous statistical techniques.

months, on average) than the previous nine (eight months, on average). Some states have long recessions and long recoveries, while other states have shorter, milder recessions and tend to recover quickly. For example, the average recession in Connecticut is 24.1 months and the average recovery is 25.1 months; on the other hand, North Dakota's recessions last about 11.9 months and it recovers in about 4.8 months. States in the Far West, Plains, and Rocky Mountain regions tend to experience fewer, shorter recessions and tend to recover more quickly.

Nevada, Rhode Island, and Wyoming typically experience the deepest contractions, with average employment losses of 0.15%, 0.16%, and 0.25% of the labor force per month in recession (respectively). Michigan (0.14%), Indiana (0.14%), and Florida (0.13%) also suffer considerable monthly employment losses during recessions. In contrast, North Dakota endures the most moderate contractions, losing only 0.05% of its labor force, on average, during each month in recession. Texas, Vermont, and Virginia also experience fairly moderate contractions, all losing only 0.07% of the labor force monthly.

2.2 Controlling for State and Recession-specific Heterogeneity

We must control for state- and recession-specific characteristics that might induce heterogeneity in the business cycle. Table 2 describes the sources of data used for estimation and provides summary statistics over all the observations in our sample.[4] We control for the length of the recession as well as the monthly employment growth in the first and second month of each state-recession experience as an indicator of the relative depth of the recession.[5] We include the shares of all other states, states in the same BEA region, and bordering states that are in recession in a one-year window as an indicator of the pervasiveness of the recession.[6]

Because many recessions are associated with energy price shocks or financial events, we include each state's oil production index (the ratio of the state's crude oil production to personal income level in 1984), the size of the net oil price increase as constructed in Hamilton (1996), and the monthly growth in the S&P 500 at the beginning of the recession.

[4] We convert select state covariates to per capita by using total state population derived from the most recent census that took place before the end of the relevant recession. For observations occurring prior to 2000, we use census data from 2000 and use 2010 otherwise.

[5] Koenders and Rogerson (2005) argue that recessions afford firms the opportunity to eliminate inefficiencies in labor usage which may have emerged over time, which can delay or extends recovery times.

[6] The BEA regions share similar business cycle experiences, supporting claims in Crone (2005) that they remain a good proxy for the construction of cyclically-synchronous regions

We control for other features of the labor market that may affect the length of unemployment spells. The fraction of each state's population with a college degree controls for more-educated individuals having possibly different rates of quits, layoffs, and hiring.[7] The share of the labor force between ages 16 and 24 may represent a more transient portion of the workforce. Larger firms may have greater access to credit and alternative sources of working capital and, therefore, may be more able to hire workers (or layoff fewer workers) during economic downturns. Thus, we control for firm size across states by including the share of total employment for firms having less than 100 employees. Because variation in the states' industrial compositions may result in heterogeneity in the depth of recessions that are propagated mainly through a specific industry, we include the annual NAICS industry shares of total payroll employment in manufacturing, construction, and finance, insurance, and real estate activities. We also include the percent of the state's total employment represented by unions, which may affect the persistence of unemployment [Barro (1988)].[8]

Home ownership may reflect potential migration costs that cause households to endure long spells of unemployment rather than move to states with better labor market conditions. We use the percentage of owner-occupied houses in each state in the decade in which the recession occurred. In addition, we control for changes in the effective mortgage interest rate between the peak and the trough in each state's recession experiences over the 1978-2012 period. The mortgage rate is obtained from the Federal Housing Finance Agency (FHFA) and we elect to look only at state recessions after 1978 due to data limitations.

Variation in state labor laws—e.g., unemployment insurance and minimum wage—can also contribute to heterogeneity in labor market conditions. Unemployment benefits are defined as the maximum number of weeks of benefits in the years state recessions ended, including standard and extended benefits triggered by state economic conditions.[9] Katz and Meyer (1990) use data from

[7] Kettunen (1997) finds that the unemployed with 13 to 14 years of education have the highest re-employment probability. Nickell (1979) and Kiefer (1985) also found a negative relationship between education and unemployment duration. Ashenfelter and Ham (1979), on the other hand, found that education had no effect on unemployment duration.

[8] Barro (1988) found that in states where union influences are not as strong, govenment spending lengthens unemployment spells. Partridge and Rickman (1997) find that states with more college graduates and fast-growing industries (relative to the national average) have lower unemployment rates. More union workers, more generous unemployment benefits or a higher percentage of homeownership also lowers state-level unemployment rate. When state-level fixed effects are included in their regressions, however, the positive effects from unions and unemployment benefits reverse signs and are insignificant.

[9] Possible endogeneity exists if workers who have exhausted regular UI benefits can extend them through the federal Emergency Unemployment Compensation (EUC) enacted in 2008. Benefits can be extended in states having sufficiently high unemployment rates for prolonged periods.

12 U.S. states and find that a one-week increase in the duration of potential benefits increases the average duration of the unemployment spells of benefit recipients by 0.16 to 0.20 weeks.[10] We also include data on the level of the minimum wage in each state. In the states with a binding minimum wage, employers may be slow to rehire, prolonging recoveries.

Finally, we include interaction terms between (1) the state's oil production index and the Hamilton net oil price increase, (2) the real minimum wage differential and the percentage of the labor force between the ages of 16 and 24, (3) the share of the workforce employed in the finance industry and the change in the S&P 500, and (4) the percentage of owner-occupied housing and the change in mortgage rates.[11]

2.3 Policy Variables

While national-level policies are common across states at the time they are implemented, differences in the timing of recessions and recoveries may alter their effects. We can also exploit the fact that some states enter recessions at different times than the nation and some states enter recessions independently of the nation. This variation allows us to identify the effect of both federal and state-level policies. To mitigate potential endogeneity associated with policy responding to extended accommodation, we consider only the stimulus that occurs during the recession, which is determined before the beginning of the recovery.

We first consider the effect of expansionary monetary policy on the length of recoveries. For each state-recession experience, monetary policy is measured as the change in the federal funds rate between the first and last months of each recession and represents the amount the Fed altered the stance of monetary policy during the recession in order to accommodate adverse shocks.

Next, we consider quarterly net federal fiscal spending, defined as the log difference of real expenditures and receipts deflated using the 2005 implicit price deflator. For each state-recession experience, we compute average net federal expenditures during the recession per quarter of the

[10] Studies of individual labor flows suggest that both national and state-level policy can alter the duration of unemployment spells. Meyer (1990) finds that higher unemployment insurance benefits prolong unemployment spells. The probability of leaving unemployment also increases sharply once the benefits lapse.

[11] The first interaction captures the notion that states with higher oil production may have different business cycle experiences for recessions caused by increases in oil prices. The second interaction captures the idea that the younger demographic may be more susceptible to minimum wage differentials. The third interaction picks up whether the effect of recessions caused by financial market disruptions is greater for states with a larger financial industry. The final interaction captures the varying effect of mortgage rates on states with higher levels of home ownership.

recession, then compute the deviation of this value from the sample average. Although national spending could respond to the length of the recovery, our assumption is that national spending does not respond to the economic conditions of individual states. Thus, the endogeneity problem is mitigated by the variation of in the length and timing of the recovery at the state level.[12]

To measure state-level net fiscal policy, we compute the log difference between state government annual expenditures and revenue per capita.[13] At the state-level, the endogeneity problem is magnified compared to that using national spending. We use real, per capita, net state-level fiscal policy for the year in which the recession began, which may not cover all of the years of the recession and recovery. The potential endogeneity between state government spending and the length of recoveries is mitigated by the fact that the spending data are annual, while the recovery times are monthly. Thus, state spending may not be able to respond in real time to a prolonged recovery.

Finally, we include a measure that captures both the existence and withdrawal rules of state-level Budget Stabilization Funds—i.e., "rainy day" funds. Wagner and Sobel (2006) construct a dataset that includes the year in which each state adopted a Budget Stabilization Fund, when deposit and withdrawal rules were placed upon the fund, and whether the fund was adopted statutorily (imposed by the legislature) or constitutionally (an amendment imposed upon the legislature through voter referendum or citizen initiative). The severity of constraints governing stabilization funds differ across states. We use the variable representing the four categories of withdrawal rules because they will determine how and when states can use the funds as stimulus during recessions, where higher values of the variable indicate stricter regulation of withdrawals.

3 Modeling the Duration of a Recovery

The business cycle is often characterized by a time-series model with nonlinearities that capture shifts in the cycle phases. We approach the problem from an alternative point of view, modeling each state-recession-recovery experience as a single observation in a time-to-event framework [Sha,

[12] For prolonged recoveries, national spending could be targeted toward states based on economic conditions, creating an endogeneity problem. We address this issue in section 5.

[13] Carlino and Inman (2013) examine whether state-level fiscal policies affect the aggregate performance of the local and neighboring economies. They find that increasing budget deficits raises local employment and that spillovers strengthen employment in neighboring states.

Tadesse, and Vannucci (2006)], where the event in question is the return to the pre-recession level of employment.[14] We then determine which policies, if any, affect the average time it takes a state to recover from a recession after controlling for economic conditions and inherent state-level characteristics.

States may have different numbers of recessions occurring at various times, making our panel unbalanced and irregular. Define τ_{nt} as the number of months for employment in state $n = 1, ..., N$ to return to its pre-recession level subsequent to a trough occurring at time t. We assume τ_{nt} is a log-normal random variable and treat each state-time recession as an independent observation. Consequently, we index each observed recovery duration by both n and t.[15]

Suppose $\log(\tau_{nt})$ is related to a $(Z \times 1)$ vector of observable covariates, x_{nt}, via a linear model:

$$\log(\tau_{nt}) = \beta_0 + x_{nt}'\beta_x + \beta_n + \varepsilon_{nt}, \tag{1}$$

where β_0 is the intercept term, β_x is a $(Z \times 1)$ vector of coefficients, β_n is a state-fixed effect for recessions that occur in state n, and $\varepsilon_{nt} \sim iidN\left(0, \sigma^2\right)$. Including the β_n term allows for controlling for unobserved state-level heterogeneity, which may affect the pace of recovery. Exponentiating (1) results in

$$\tau_{nt} = \exp\left(\beta_0 + x_{nt}'\beta_x + \beta_n\right) w_{nt}, \tag{2}$$

where $w_{nt} = \exp(\varepsilon_{nt})$. Thus, the failure times have a baseline hazard function $\lambda_0(w_{nt})$ that is independent of the linear predictor term $(\beta_0 + x_{nt}'\beta_x + \beta_n)$. The hazard function, $\lambda_{nt}(\overline{\tau})$, denotes the probability that the recovery ends after the $\tau_{nt} = \overline{\tau}$ month, conditional on it lasting at least that long, and is defined by

$$\begin{aligned} \lambda_{nt}(\overline{\tau}) &= \lim_{h \to 0^+} \frac{\Pr[\overline{\tau} + h > \tau_{nt} \geq \overline{\tau}]}{h} \\ &= \frac{\lambda_0(w_{nt})}{\exp(\beta_0 + x_{nt}'\beta_x + \beta_n)}. \end{aligned}$$

[14] The widely-used Cox (1972) Proportional Hazards model assumes a multiplicative effect of the covariate on the hazard probability rather than imposing a direct relationship between the covariate and the duration. Thus, interpretation of the effect of the covariate less straightforward. Furthermore, variable selection for the AFT model is simplified because the coefficients can be integrated out of the posterior likelihood.

[15] Although the recoveries will be indexed by t, we do not explicitly model the evolution of the recoveries over time except through the set of possibly time-dependent covariates. We could index the recoveries by a count variable (say, $k = 1, ..., K$) but prefer the time index for exposition.

The baseline hazard $\lambda_0(w_{nt})$ applies in the absence of any explanatory covariates. The covariates have a multiplicative effect on τ_{nt}, accelerating or decelerating the time to recovery, rather than on the hazard (as in the Cox model).

There may be occasions when the employment level does not return to the pre-recession high before another recession occurs. We treat these recovery events as right-censored at the beginning of the subsequent recession. The censored observations still have some information, since we know that the recovery lasted at least that long. As in Sha, Tadesse, and Vannucci (2006), we adopt the approach of Tanner and Wong (1987) to impute the censored duration. Let C_{nt} be the time between state n's trough occurring at time t and its next recession occurring at time $t + C_{nt}$. We can define an indicator δ_{nt} such that $\delta_{nt} = 1$ if the end of the spell is observed (i.e., if $\tau_{nt} \leq C_{nt}$) and $\delta_{nt} = 0$ if the observation is right-censored (i.e., if $\tau_{nt} > C_{nt}$). Define $Y_{nt} = \min\{\tau_{nt}, C_{nt}\}$, which reflects the *observed* recovery duration associated with state n's period t trough. Let $\boldsymbol{\tau}$ be the vector of recovery times which may include both observed and unobserved recovery times, where

$$\log(\tau_{nt}) = \begin{cases} \log(Y_{nt}) & if \quad \delta_{nt} = 1 \\ TN\left(\beta_0 + x_{nt}'\beta_x + \beta_n, \sigma^2, \log(Y_{nt}), \infty\right) & if \quad \delta_{nt} = 0 \end{cases} \tag{3}$$

that reflect either the full duration of the recovery or the observed recovery period before censoring, where $TN(,.,.,.)$ is a normal left-truncated at $\log(Y_{nt})$.

3.1 Covariate Selection

Because we wish to test many (possibly competing) hypotheses and control for a large number of possible state- and time-specific characteristics, the number of covariates can be large. We want to remove potential contaminating effects of the state characteristics and focus specifically on the effects of different policy actions on the length of recoveries. However, there is little consensus regarding which state characteristics are most important and should be included. Therefore, we include all policy variables in each regression and design a covariate selection algorithm to determine which controls should be included.

Define $\mathbf{X}_{nt}$ as the vector of all covariate data for each state-recession experience, including the intercept and the state-level fixed effect and define $\beta = [\beta_0, \beta_x', \beta_n']'$. The dimension of $\mathbf{X}_{nt}$ is

$M = ((Z + N + 1) \times 1)$ as it includes the intercept term, the Z potential observable covariates and the N state-fixed effects. Let $m_i \in \{0, 1\}$ represent the indicator associated with the ith element of the covariate vector, $\mathbf{X}_{nt}^i$. If $m_i = 1$, $\mathbf{X}_{nt}^i$ is included in the model; if $m_i = 0$, it is excluded. We can collect the model indicators into a vector m and rewrite the log recovery time as a function of the full set of covariates and m:

$$\log(\tau_{nt}) = (m \odot \mathbf{X}_{nt})'\beta + \varepsilon_{nt}, \tag{4}$$

where m is invariant to the state n and the recession occurrence t.

In practice, estimation of the model indicator will yield the posterior probability that $\mathbf{X}_{nt}^i$ is included in the model. One advantage of using the model indicators is that the mode model (i.e., the model for which the mode of the posterior distribution of m is computed) has a dimension (often substantially) less than M. In addition, because the actual recovery time τ_{nt} is a nonlinear function of the explanatory data, including an irrelevant covariate can influence the marginal effect of other variables even if the coefficient on the irrelevant covariate is very small. The first element of m corresponds to the intercept term and is always set equal to 1 so it is included in every proposed model. Additionally, the elements of m corresponding to the policy measurements are always set to 1 in order to include all policy variables in each regression, through all iterations of the sampler. This has the added benefit of easily constructing the posterior of the policy variables since we draw their coefficients in each iteration and use the full set of draws for posterior inference.

3.2 Estimation

The model is estimated using Bayesian methods. The Bayesian framework implements covariate selection in a straightforward manner and has the advantage of allowing us to impose priors on the model parameters, including the model indicators. For example, we could construct a parsimonious set of influential factors by putting a high prior probability on excluding each covariate. We specify conjugate priors for the model parameters, which allows us to integrate out the regression coefficients when deriving the marginalized likelihood and speed up the model-fitting procedure considerably. To generate the joint posterior for the full set of model parameters, we use the Gibbs sampler [Carter and Kohn (1994); Casella and George (1992)] with a Metropolis-in-Gibbs step to jointly draw the model inclusion dummies with the model parameters. The Gibbs sampler is a Markov-chain Monte Carlo (MCMC) technique that iteratively draws from the posterior of one block of model parameters, conditional on the previous draw of the other model parameters.

We employ a fairly standard prior. The β's have a normal prior that is assumed to be independent across the covariates and is relatively more diffuse for the intercept, $\beta \sim N\left(b_0, \sigma^2 B_0\right)$, where $b_0 = 0$, $B_0 = diag\,(h)$, and $h = [100, 1, ..., 1]_{1\times M}$. The innovation variance has an inverse gamma prior, $\sigma^2 \sim IG\left(\frac{v_0}{2}, \frac{v_0 \sigma_0^2}{2}\right)$, where $v_0 = 3$ and $\sigma_0^2 = 1$. The model inclusion parameters have a Bernoulli prior with equal weight on inclusion and exclusion: $m_i \sim Bernoulli\,(p)$, where $p = 0.5$.

After discarding 100,000 draws to achieve convergence, the collection of 200,000 iterative draws approximates the full joint posterior for all model parameters. The Appendix provides a detailed discussion of the Gibbs sampler.

3.3 Interpreting β

The recovery time for a given state-recession experience can be predicted by utilizing a model-averaging technique similar to those presented in Madigan and Raftery (1994) and Brown, Fearn, and Vannucci (1998). We can compute the expected difference between two state-recession experiences that differ only by a one-unit increase in $x_{nt,k}$, holding all other components of x_{nt} fixed.[16] The survival times, τ_{nt} and τ_{nt}, corresponding to $x_{nt,k}$ and $x_{nt,k} + 1$, respectively, are

$$\tau_{nt} = \exp\left(\beta_0 + x_{nt,k}\beta_{x,k} + x'_{nt,-k}\beta_{x,-k} + \beta_{s,n}\right) w_{nt} = c_1 w_{nt}$$

and

$$\tau_{nt} = \exp\left(\beta_0 + (x_{nt,k} + 1)\beta_{x,k} + x'_{nt,-k}\beta_{x,-k} + \beta_{s,n}\right) w_{nt} = \exp\left(\beta_{x,k}\right) c_1 w_{nt},$$

where $x_{nt,-k}$ is the x_{nt} vector excluding element $x_{nt,k}$ and $\beta_{x,-k}$ is the β_x vector excluding $\beta_{x,k}$. Thus, increasing $x_{nt,k}$ by one unit increases the expected duration by a factor of $\exp\left(\beta_{x,k}\right)$. If $\beta_{x,k}$ is relatively small, this factor can be approximated by:

[16] We standardize all covariate data across state-recession observations to be mean zero with unit variance. Therefore, a one-unit increase in $x_{nt,k}$ corresponds to a one-standard-deviation increase in that covariate.

$$\frac{\tau_{nt} - \tau_{nt}}{\tau_{nt}} = \exp\left(\beta_{x,k}\right) - 1 \approx \beta_{x,k}.$$

and we can interpret $\beta_{x,k}$ as the percentage increase in the expected duration of recovery, given x_{nt}, associated with a one-unit increase in $x_{nt,k}$.

Note that the marginal effect of a change in $x_{nt,k}$ is a proportional change and depends on the initial conditions x_{nt} at the time of the policy implementation. Thus, the effect on recovery times is different from linear or piecewise linear (e.g., Markov switching) models for which policy innovations would be time-invariant or depend only on the exogenous regime. In this sense, our model allows more explainable heterogeneity in the policy effects based on how deep or long the recession was, the magnitude of the policy intervention, and the characteristics of the state's economy.

4 Results

Results of the estimation of the baseline recovery duration model of Section 3 using the Bayesian method outlined above are shown in Table 3. The first column provides the inclusion probabilities for the state-recession characteristics in the baseline model and the mean of the coefficient estimates weighted according to the normalized posterior probability of potential model $m^{(k)}$; a bold **1** for the policy variables' inclusion probabilities indicates that there are set ex ante. A positive β implies that the expected log recovery time increases as the covariate x_{nt} increases.

4.1 State and Recession Effects

Those covariates with high probability of inclusion (close to 1) are (1) the length of the recession, (2) other states in the same BEA region also in recession, (3) the max oil shock, (4) the percentage of the state's adult population with at least a Bachelor's degree, and (5) the percentage of the state's workforce employed in the finance, insurance, and real estate (FIRE) industries. We include state-level fixed effects and find that the marginal probabilities of including them are greater than 20% for most of the states, with 11 states above 50%. Additionally, the interaction between the max oil shock and the oil share index has a 0.75 probability of inclusion with a positive coefficient and, thus, is associated with longer recoveries. Surprisingly, higher unemployment benefits do not seem to affect recovery times in either direction as the covariate is only included in 5% of the draws.

The first three results are straightforward: Longer (peak to trough), deeper (relative to peak), and more pervasive (spread across more states) recessions require longer recovery times. For example, a one-standard-deviation (8.4 months) longer-than-average recession is associated with a 61% longer-than-average recovery time. Oil price shocks are associated with deeper recessions and, thus, tend to prolong recoveries. Thus, a one-standard-deviation oil price shock—approximately a 4% increase above the previous 12-month maximum oil price—extends the average recovery time by 23%. The interaction between the oil share index and the net oil shock also slows recovery times suggesting that states that rely heavily on oil production are, on average, more vulnerable to oil price shocks. Those states heavily invested in oil production seem to be hit the hardest when recessions follow sizeable oil shocks. The fourth result is less straightforward but might be explained if highly-educated workers are more selective in searching for new jobs.[17] The coefficient on the share of the workforce in the FIRE industries is negative, suggesting a larger share of financial firms tends to shorten recovery times.

4.2 The Effect of Policies on Recovery Times

Having controlled for variation in the state and state-recession characteristics, we now consider the effect of countercyclical policies intended to stimulate the economy in times of recession. Table 4 describes the expected change in recovery time in response to policy changes. We interpret the coefficient from the AFT model estimation in terms associated with realistic changes in countercyclical policy that might be expected to occur during recessionary periods. Because the model is nonlinear, in that the effects of policy are dependent upon the prevailing economic conditions at the time of implementation, we highlight a number of scenarios reflecting differences in both economic and policy conditions.

First, we set the state characteristics, the S&P 500 variable, and the share of other states in recession to their mean values within the sample. The max oil shock is set to zero. Then, we adjust the recession length and policy variables to reflect interesting environments for analysis. We set the recession length to (i) its mean, (ii) one standard deviation above the mean (long), or (iii) one standard deviation below the mean (short). "Policy Conditions" indicate the values of our policy

[17] Herkenhoff (2013) finds that lower income individuals are more limited in their access to credit cards and are more willing to accept less attractive job offers, while higher income workers are more likely to be approved for credit cards, have a more valuable outside options, and can be more selective in accepting job offers.

variables before any shocks: Accommodative (tight) policy setting represents state and federal fiscal spending one standard deviation above (below) their mean values and the federal funds rate one standard deviation below the mean. For each case, except when explicitly stated, we set the Budget Stabilization Fund (BSF) variable to zero.

The first row provides the expected recovery time (in months) for the specific economic and policy conditions specified under each scenario without policy shocks. The expected recovery can range from 10.41 months for short recessions under tight policy conditions to 60.56 months for long recessions and accommodative policies. We then compute the effects of policy as the percentage change based upon these expected recovery times. The "Policy Change" rows show the effects of a countercyclical change in each policy of a magnitude that may be relevant for combating recessions.

First, consider the state-level policies. The results from the baseline model suggest that the severity of constraints on making withdrawals from a state's budget stabilization fund does not have a significant effect on recovery times. The variable measures the restrictions on withdrawing from the fund; thus, the estimated sign of the coefficient is consistent with previous results that stricter rules on withdrawals lead to more effective policies that are more likely to reduce recovery times after recessions. Table 4 illustrates that a more restrictive rule can shorten the expected recovery time by 0.77 months under average conditions. The effect ranges from 0.32 months for short recessions and tight policy conditions to 1.85 months for long recessions and accommodative policies.

We find that an increase in net spending during the recession is associated with an increase in the duration of the recovery. An estimated coefficient of 0.23 suggests that a one-standard-deviation increase in state fiscal spending lengthens recoveries by around 23%. We use this to convert the policy effects to consider a 10% increase in state fiscal spending, a reasonable magnitude for policy action during a recession. For recessions at the mean length, with average policy conditions, a 10% increase in state fiscal spending would be associated with recoveries lasting 2.83 months longer. The relationship is magnified when one considers long recessions under accommodative policies– increasing state fiscal spending by 10% would lengthen the expected recovery by 6.83 months. We consider the potential endogeneity of fiscal spending further below when discussing federal fiscal policy.

The next set of marginal effects considers federal monetary and fiscal policies. While monetary policy is set in response to aggregate economic conditions, because states may move into and out of recession independently from the nation, monetary policy's implementation at the national level makes it unsuitable to facilitate a particular state's individual recovery experience. Monetary policy, however, is effective when a number of states move together. We find that monetary policy has the desired countercyclical effects: A reduction in the level of the federal funds rate during the recession reduces a state's expected recovery time. The magnitude of this coefficient, 0.10, suggests that a one-standard-deviation cut in the federal funds rate (about 280 basis points) during the recession shortens recovery time by about 10%. Table 4 converts this outcome to consider the effect of a 100-basis-point reduction in the federal funds rate. Further easing of policy during long recessions with already accommodative policies would reduce the expected recovery time by a little over 2 months (2.15). However, for a short recession under initially tight policy conditions—perhaps representative of idiosyncratic state recessions where the national policymakers do not take aggressive action—cutting the federal funds rate by 100 basis points only shortens the expected recovery time by 0.37 months.

Fiscal policy, like monetary policy is implemented at a national level. Unlike monetary policy, national spending can affect a state either by stimulating the national economy (as in the rising tide) or by increasing spending in targeted areas. In this section, we consider the former; we address the latter issue in Section 5. Similar to our findings for the state-level fiscal policy, an increase in net spending during the recession is associated with an increase in the duration of the recovery. More specifically, the coefficient in Table 3 of 0.14 implies that a one-standard-deviation increase in federal spending lengthens the expected recovery by 14%. Table 4 converts this in the same way as we did for state spending: a 10% increase in quarterly federal spending is associated with an additional 3 months of recovery time for average recessions. Again, for long recessions with accommodative policies, federal spending would now be linked to extending recoveries by 7.41 months. We attempted to control for the endogenous response of policy to the length of the recovery by using only spending during the recession; however, because the severity of the recession is correlated with the duration of the recovery, net spending during the recession may still be endogenous. We reconsider fiscal policy, along with a few other robustness checks, below.

5 Robustness

The preceding results suggest that expansionary monetary policy during the recession is the only policy tool that shortens the duration of the recovery. In this section, we consider some modifications to the baseline model that test the robustness of our conclusions. First, we redefine the recessions and recoveries using an alternative business cycle indicator, the state-level unemployment rate. Then, we examine alternative policy measures.

5.1 Alternative Business Cycle Indicators

When constructing the recession dates for the national economy, the NBER Business Cycle Dating Committee uses multiple indicators. For the states, many of these indicators are not timely, not high enough frequency, or are not available at all.[18] One particular indicator that garners a lot of attention is the unemployment rate. Among other potential labor market indicators (e.g., household employment), the unemployment rate is the least correlated with payroll employment, possibly due to the flows in and out of the labor market causing fluctuations in participation. The average of the states' correlations between payroll employment and the unemployment rate in the sample is -0.444.

To verify the robustness of our results, we compare the results using payroll employment to results using the unemployment rate. We redefine recessions using the troughs and peaks of the unemployment rate, identifying six of eight consecutive months when the unemployment rate is rising as recessions. We define the recovery times as the number of months until the unemployment rate returns to its pre-recession level. Using this recession dating method for the unemployment data and comparing with employment recessions, the average recession and recovery concordances across states are 0.862 and 0.736, respectively.

Table 5 compares the results using the unemployment rate to the baseline case for the policy variables; results for the control variables were qualitatively unchanged and are not represented here. Changes in the fed funds rate during the state's recession have somewhat stronger countercyclical effects, compared with the baseline. Cutting the fed funds rate by around 318 basis points (a

[18]The conventional indicator of output—state-level GDP—is observed only annually and, thus, would not provide an adequate measure of the duration of recoveries. Another alternative is the Federal Reserve Bank of Philadelphia's state-level Coincident Indicators (https://www.philadelphiafed.org/research-and-data/regional-economy/indexes/coincident/). These indices, again, are largely estimated from labor market data.

larger standard deviation than the monetary accommodation observed with the baseline recessions) reduces the average recovery time by 26%. Two qualitative differences stand out: Net fiscal spending at the national level now has a significantly negative impact on the length of recoveries and changes in net fiscal spending at the state level are no longer significant.

5.2 Differences in the Policy Measures

We constructed measures of expansionary policy intended to be exogenous to the length of the recovery. In the next few subsections, we verify the robustness of our conclusions using some alternative measures of policy. Table 6 summarizes the results of each of these robustness tests. Additionally, we conduct the same exercise as we did for the baseline by converting the policy effects into magnitudes that may be relevant for countercyclical policy analysis, under the same recession/policy conditions as discussed in Section 4.2. These results are reported in Table 7.

5.2.1 Policy During the ZLB Period

Our measure of monetary policy is motivated by the empirical literature [Christiano, Eichenbaum, and Evans (1996) and Bernanke and Mihov (1998)]. One possible complication is that, starting in 2008, the federal funds rate hit the zero lower bound (ZLB) and, thus, may not be a proper measure of the stance of monetary policy during that period. Recent studies [Krippner (2015) and Wu and Xia (2016)] suggest that the shadow short rate constructed from a hypothetical zero-term bond in a Gaussian affine term structure model can capture the stance of policy when the nominal short rate is bounded. The shadow short rate relates to the federal funds rate as follows: When the fed funds rate is significantly above the ZLB, the two are equal; when the fed funds rate is at the ZLB, the shadow short rate can become negative, suggesting a heightened level of monetary accommodation.

We use the shadow short rate constructed by Wu and Xia available from the Federal Reserve Bank of Atlanta. The second column of Table 6 reproduces the results for the policy variables from the baseline model estimation for reference. The third column shows how the results change when the federal funds rate is replaced with the shadow short rate. The differences are only minor, with monetary policy being only slightly less effective when measured by the change in the shadow short rate. Table 7 further emphasizes this point: for long recessions under accommodative policy conditions, a 100-basis-point cut in the shadow rate reduces expected recovery times by slightly less than the baseline case: 1.93 months versus 2.15 months in the baseline.

5.2.2 Narrative Shocks

In the preceding sections, we found that an increase in net government spending during the recession—be it at the national or state level—is associated with an increase in the duration of the recovery. This result gives rise to the obvious concern that net spending is endogenous, rising during particularly deep or long recessions, leading to a positive correlation with the length of the recovery. For example, net spending could rise during a prolonged recession as unemployment benefits are extended. Disentangling the response to exogenous shocks to spending from these endogenously triggered responses is important for understanding how fiscal policy affects the recovery. Thus, we consider an additional narrative measures of fiscal policy: the Romer and Romer (2010) tax variable.[19] For this exercise, we look only at recessions which ended prior to December 2007 due to data availability.

The fourth column of Table 6 presents the baseline results for the period from 1978 through the end of 2007 for comparison. One notable difference between these results and the baseline results with the full sample is that the effect of monetary policy is a bit weaker; 0 is included in the 90-percent coverage interval but it excluded from the 68-percent coverage interval. Another notable difference is that stricter state-level budget stabilization funds also appear to reduce recovery times prior to the Great Recession. For comparison, the top section of Table 7 illustrates the change in expected recovery times for policy changes of the same magnitudes as those discussed for the baseline model.

The fifth column of Table 6 shows the results we obtain by adding the Romer and Romer exogenous tax changes. In this case, when we have an exogenous measure of tax policy, we find that decreasing taxes leads to a decrease in the length of the recovery. In Table 7, we consider a tax cut equal to 10% of GDP. The predicted reduction in recovery times ranges from 3.18 months for short recessions under tight policy conditions, to 11.82 months for long recessions under accommodative

[19] We compute the average monthly exogenous tax change during state-recession as the sum of exogenous tax changes over state-recession identified in Romer and Romer (2010), divided by the length of recession (in months). The Romer and Romer tax data are available through 2007:IV so we exclude state-recessions which begin in 2008:I and later.

policies. Consistent with the baseline results, a drop in the fed funds rate during the recession also reduces the duration of recoveries.

5.2.3 Targeted Military Spending

Another way to handle the potential endogeneity problem in the fiscal data is to exploit the cross-state variation in how national spending is allocated. To do this, we use the military procurement measure of Nakamura and Steinsson (2014).[20] These data reflect exogenous changes in military procurement spending in a particular state and are available through 2006; we exclude state-recessions which begin in 2007 and later. Because the data are annual, we assign the value associated with the year in which the state-recession begins.[21]

The sixth column of Table 6 shows the results when adding the targeted military spending variable to the baseline model with net federal fiscal spending. We find that an exogenous increase in military procurement in the state lowers the duration of that state's recovery period. This result, coupled with the previous result on tax changes, suggest that exogenous fiscal shocks—along with monetary accommodation and, perhaps, strict rainy day funds—can reduce recovery times.

This measure of fiscal policy produces countercyclical effects: States receiving a larger amount of military spending benefit from shorter recovery times. The magnitude of this coefficient, -0.16, suggests that a one-standard-deviation increase in military procurement spending received by the state (about 0.4% of state GDP) during the year in which the recession begins shortens the expected recovery time by about 16%. For a conservative interpretation of these results, in Table 7, we consider an increase in targeted military spending of 0.1% of the state's GDP. For an average recession under policy conditions set to the mean, this would reduce the expected recovery by just under one month (0.79). If instead a state receives this funding during a long recession under otherwise tight policy conditions, the expected recovery shortens by 1.61 months.

[20] Carlino and Inman also look at differential Carlino and Inman (2014) consider differential federal expenditures to state and local governments. Their measure, however, is based on total welfare and project aid, which is likely to be endogenous. As we expected, when we estimate a model with the Carlino and Inman meausre, we find results similar to our baseline model: The estimated coefficient is significantly positive for all three of their measurements of federal fiscal aid to states, suggesting that their measure is indeed endogenous.

[21] We use the authors' code to obtain the fitted values from the first-stage regression in Nakamura-Steinsson's two-stage-least-squares IV estimation. This first stage regresses each state's two-year change in real, per-capita military procurement spending on changes in national per-capita procurement spending and state and time fixed effects. State and national spending measurements are expressed as a percentage of either state or national output, respectively.

5.2.4 Targeted ARRA Spending

In the previous sections, we found that the effects of fiscal policy could depend on when it was measured. If we measure the effect of fiscal policy prior to the Great Recession, we find that an increase in spending can reduce the recovery time; the opposite result obtains if we include the Great Recession. Unfortunately, our two exogenous measures are not available for the Great Recession period. We can, however, exploit the variation in the amount of the spending of the American Recovery and Reinvestment Act of 2009 (ARRA) received by each state.

We can augment the baseline regression by weighting the fiscal spending variable by the ARRA weight for recessions that occur after the onset of the Great Recession.[22] The seventh column of Table 6 shows this result. We find that when national spending is properly weighted—in this case, by the proportion of national spending allocated to the state by the ARRA, net fiscal spending does reduce the duration of the recovery. As a share of the total ARRA spending, states on average received around $10 billion. Table 7 illustrates that this amount of targeted spending shortens expected recovery times by almost 5 months (4.90) for the mean recession length under the mean policy conditions. The ARRA spending was implemented during what likely would be characterized as longer, deeper recessions and during a period in which most countercyclical policies were quite aggressive. For long recessions in an accommodative policy environment, $10 billion of ARRA spending reduces the expected recovery time by almost one year (11.71 months). This result confirms the notion that exogenous targeted net spending can be effective but raising the overall level of spending for all states is ineffective, and may be associated with longer recovery periods.

6 Conclusions

We estimate an accelerated failure time model to analyze the required time for recovery after recessions in individual U.S. states. In controlling for state-level characteristics and recession-specific conditions, we assess the efficacy of state and federal policies at stimulating state-level economies and shortening recovery times. Perhaps not surprisingly, we find that recessions that are

[22] We use data on the state-level disbursement of ARRA funds during the Great Recession available at http://projects.propublica.org/recovery/. The ProPublica database uses recipient-reported data from Recovery.gov and Recovery Act grants and loans reported by government agencies on USAspending.gov. For all state-recession observations that occur within the timing of the ARRA stimulus program, we use the total value of federal stimulus directed to a given state.

long in duration and occur simultaneously in multiple states within the same BEA region require significantly longer recovery periods. However, these recoveries can be shortened through the proper implementation of monetary policy by the central bank.

We model states as being able to move into recessionary periods independently of the nation. Therefore, we recognize that monetary policy, being a national instrument for a currency union, does not respond specifically to recessions in individual regions. The central bank sets policy in response to national economic conditions and may not pay attention to regional business cycles except to the extent that they determine aggregate behavior. Nonetheless, the level of overall policy accommodation during state recessionary periods does appear to help speed up recoveries.

We also find that national-level increases in net spending during the recession—i.e., increases in spending or decreases in taxes—appear to be correlated with increased recovery times suggesting that spending is endogenous. However, when measured by exogenous changes in taxes or by measuring directly the amount of spending on a particular state, the effect of fiscal policy is to reduce recovery times.

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State	Number of Recessions	Avg. Recession (months)	Avg. Recovery (months)	St. Dev. of Recoveries	Avg. Monthly Employment Loss (% of Labor Force)
Alabama	12	14.08	8.58	4.94	0.08%
Arkansas	11	14.27	10.73	10.36	0.08%
Arizona	8	14.75	9.50	8.65	0.10%
California	9	17.11	18.00	12.75	0.08%
Colorado	5	20.80	22.80	7.85	0.09%
Connecticut	11	24.09	25.09	23.73	0.11%
Delaware	9	17.78	17.89	14.84	0.09%
Florida	5	17.40	16.20	11.17	0.13%
Georgia	9	15.22	14.22	12.76	0.09%
Iowa	10	16.00	15.60	15.38	0.08%
Idaho	8	15.13	14.13	10.48	0.11%
Illinois	10	20.60	22.80	17.24	0.10%
Indiana	13	16.31	15.54	10.41	0.14%
Kansas	10	16.20	17.60	16.61	0.11%
Kentucky	9	16.44	17.78	12.69	0.09%
Louisiana	10	18.60	18.70	11.49	0.08%
Massachusetts	11	21.45	21.36	19.82	0.11%
Maryland	7	19.14	21.29	15.62	0.09%
Maine	10	17.30	17.80	13.72	0.10%
Michigan	12	19.33	14.42	8.27	0.14%
Minnesota	8	14.50	11.00	8.49	0.09%
Missouri	13	14.69	15.77	9.93	0.09%
Mississippi	12	15.67	9.67	6.12	0.08%
Montana	11	13.27	12.27	10.69	0.09%
North Carolina	11	15.45	11.00	7.82	0.09%
North Dakota	8	11.88	4.75	4.95	0.04%
Nebraska	5	14.00	14.40	13.39	0.08%
New Hampshire	7	19.29	24.71	15.57	0.12%
New Jersey	7	21.43	25.43	17.33	0.11%
New Mexico	5	12.40	9.20	8.11	0.09%
Nevada	6	19.83	13.50	8.69	0.15%
New York	15	15.80	15.27	17.90	0.08%
Ohio	12	19.67	18.92	9.92	0.12%
Oklahoma	11	15.45	15.64	14.23	0.08%
Oregon	10	17.30	15.00	11.39	0.11%
Pennsylvania	14	16.43	17.29	10.25	0.10%
Rhode Island	15	17.80	14.93	10.86	0.16%
South Carolina	10	18.90	17.90	12.57	0.09%
South Dakota	8	15.13	9.13	9.23	0.08%
Tennessee	11	15.27	14.36	11.28	0.09%
Texas	8	15.75	11.50	6.50	0.07%
Utah	7	16.29	11.57	10.85	0.09%
Virginia	10	15.40	14.20	11.74	0.07%
Vermont	12	13.67	9.50	11.21	0.07%
Washington	10	15.70	17.10	13.05	0.09%
Wisconsin	13	14.69	8.92	4.13	0.10%
West Virginia	13	15.00	18.00	21.15	0.13%
Wyoming	6	16.83	25.50	17.95	0.25%
United States	12	11.00	14.33	11.57	0.14%

Table 1: Characteristics of recessions and recoveries in each of the 48 contiguous U.S. states used for estimation. We define a state in recession when employment falls for at least six of eight consecutive months. The peak is the month immediately preceding the recession and the trough is the final month of the recession. We characterize a recovery as the number of months, following the trough, to reach the pre-recession level of employment. Column 2 shows the number of recessions in each state from 1939 to 2012. Columns 3 and 4 show the average length of recession and recovery, respectively. Column 5 shows the standard deviation (in months) of the length of recoveries. Column 6 shows the average employment loss per month of recession, as a percentage of the average size of the labor force over the years 1990-2006.

Covariate	Transformation	Period	Mean	St. Dev.	Source
State Characteristics					
Bachelor's degree or more	% of population 25 years old and over	1940-2010	-0.35	3.95	US Abstract
	Deviation from national mean in the year each recession ends				
Share of labor force ages 16-24		1940-2010	0.15	0.02	BLS
Median Household Income		1940-2010	50,577	8,648	BLS
Oil production index		1946-2012	3.04	7.73	Hamilton/Owyang
Labor Market					
% of emp. in firms with < 100 employees		1990-2010	0.31	0.06	BLS
% of emp. in manufacturing industry	Annual NAICS industry shares of total payroll employment	1990-2010	0.22	0.15	BLS
% of emp. in financial activities industry		1990-2010	0.06	0.02	BLS
% of emp. in construction industry		1990-2010	0.05	0.01	BLS
% of emp. with union membership	Value from 2000 or 2010 (for recessions pre/post-2000)	2000-2010	0.13	0.05	BLS
Unemployment benefits	Maximum total number of weeks of unemployment benefits	1940-2012	30.06	7.61	DOL
State minimum wage	Inflation-adjusted difference between state and federal minimum wage	1968-2012	-0.39	0.99	DOL
Housing Industry					
Owner-occupied housing	% of owner-occupied houses in the decade the recession occurred	2000-2010	0.68	0.05	Census
Effective mortgage interest rate	Change in mortgage rate between the peak and trough of each recession	1978-2010	0.02	0.00	FHFA
Overall Economic Conditions					
Net oil price increase (oil shock)	Sum of max oil price shocks during recession	1946-2012	0.02	0.04	WTI/Hamilton
S&P 500 stock price index	Growth rate at the beginning of the recession	1957-2012	-2.33	5.75	FRED
Policy					
State Government Policy					
Net state fiscal spending	Log difference in real per capita government expenditure and revenue	1950-2010	0.04	0.20	US Abstract
Budget stabilization fund (BSF)	Withdrawal rule for years in which the fund was in place		1.47	1.25	Wagner/Sobel
Federal Government Policy					
Effective federal funds rate	Change between first and last month of the rececession	1954-2012	-3.55	2.83	FRED
Net federal fiscal spending	Average quarterly net real fiscal spending over the recession	1947-2012	0.08	0.11	FRED
Romer-Romer tax shocks	Average monthly exogenous tax change during recession	1945-2007	-2.34	4.96	Romer/Romer
Nakamura-Steinsson military spending	Percent change in real, per-capita state spending	1966-2006	0.0007	0.003	Nakamura/Steinsson

Table 2: Covariate data sources and summary statistics for all state-recession observations in the sample. Sources are abbreviated as follows: FRED - St. Louis Federal Reserve Bank FRED database; Census - U.S. Census Bureau; US Abstract - Statistical Abstract of the US; StatsUS - Statistics of U.S. Businesses data set ; BLS - Bureau of Labor Statistics ; DOL - Department of Labor ; FHFA - Federal Housing Finance Agency ; Hamilton/Owyang - Hamilton and Owyang (2012) ; Wagner/Sobel - Wagner and Sobel (2006) ; WTI - West Texas Intermediate oil price data / Hamilton (1996). ; Romer/Romer - Romer and Romer (2010) ; Nakamura/Steinsson - Nakamura and Steinsson (2014)

Covariate	Marginal Prob. of Inclusion	Model Prob. Weighted Mean
State Characteristics		
Bachelor's Degree - Deviation from Mean	0.95	0.20*
% Labor Force Ages 16-24 (LF1624)	0.01	0.00
Median Household Income	0.06	0.01
Labor Market		
Small Firm	0.03	0.00
Manufacturing Share	0.00	0.00
Financial Share	0.96	-0.23*
Construction Share	0.02	0.00
% Union	0.01	0.00
Real Difference in Minimum Wage from Federal	0.01	0.00
Real Minimum Wage Difference x LF1624	0.01	0.00
Max Weeks Unemployment Benefits	0.05	0.00
Housing Industry		
% Own Home	0.03	0.00
Change in Mortgage Rate - Peak to Trough	0.02	0.00
% Own Home x Change Mortgage Rate	0.02	0.00
Overall Economic Conditions		
Recession Length	1.00	0.61*
Other States in Rec - USA	0.01	0.00
Other States in Rec - BEA Region	0.97	0.21*
Other States in Rec - Border	0.05	0.01
Max Oil (Hamilton)	1.00	0.23*
Max Oil x Oil PI	0.75	0.10*
SP500 Growth at Beginning of Recession	0.00	0.00
Financial Share x SP500 Recession	0.01	0.00
Employment Growth - 1st Month of Recession	0.01	0.00
Employment Growth - 2nd Month of Recession	0.00	0.00
Policy		
State Government Policy		
Budget Stabilization Fund Withdrawal Rule	**1**	-0.03
State Fiscal Spending	**1**	0.23*
Federal Government Policy		
FFR Change Over Recession	**1**	0.10*
Net Fiscal Spending Over Recession	**1**	0.14*

Table 3: Estimation Results for the Accelerated Failure Time Model. The table shows the marginal probability of inclusion (the posterior probability that the covariate should be included in the model) and the model probability weighted mean (eq. (11)) of the cofficients for the model given by eq. (4) estimated with recessions and recoveries defined by employment. Covariates are listed in Table 2. Bold 1 indicates the probability is set to 1. * Indicates that the Marginal Probability of Inclusion exceeds 20% and the 90% Posterior Coverage interval excludes zero.

Marginal Effects: Baseline								
Recession Length		Mean	Long	Short	Long	Short	Long	Short
Policy Conditions		Mean	Mean	Mean	Accommodative		Tight	
Expected Recovery (Months)		25.11	46.42	13.58	60.56	17.72	35.58	10.41
Policy Variable	**Relevant Policy Changes**	**Change in Expected Recovery Time**						
State Government Policy								
BSF Withdrawal Rule	More restrictive withdrawal rules	-0.77	-1.42	-0.42	-1.85	-0.54	-1.09	-0.32
State fiscal	10% increase in net state fiscal spending	2.83	5.24	1.53	6.83	2.00	4.01	1.17
Federal Government Policy								
FFR	100 basis point reduction over recessionary period	-0.89	-1.65	-0.48	-2.15	-0.63	-1.26	-0.37
Federal Fiscal	10% increase in average quarterly net fiscal spending	3.07	5.68	1.66	7.41	2.17	4.36	1.27

Table 4: Marginal Effects. The table shows the change in the expected duration of the recovery time (in months) for the estimated model in eq. (4) when changing one of the four policy variables. Because the model is nonlinear, we show a number of scenarios reflecting differences in intital conditions. For all scenarios, state characteristics, S&P variables, and the number of other states in recession are set at their means (see Table 2) and max oil is set to zero. Recession lengths are set to mean, 1 std above (long), and 1 std below (short). "Policy Conditions" indicates the values of the policy variables: mean, accommodative (1 std above the mean for state and federal fiscal spending, 1 std below the mean FFR), or contractionary (1 std below the mean for state and federal fiscal spending, 1 std above the mean FFR). Except when explicitly stated, the BSF variable is set to zero. The table shows the change in expected duration of recovery for (1) an increased restrictiveness in the BSF withdrawal rule, (2) a 10% increase in state fiscal spending, (3) a 100-basis-point reduction in the FFR, and (4) a 10% increase in federal fiscal spending from the initial conditions indicated by "Policy Conditions".

Covariate	Baseline	Unemployment Rate
	Model Prob. Weighted Mean	Model Prob. Weighted Mean
Policy		
State Government Policy		
Budget Stabilization Fund Withdrawal Rule	-0.03	0.00
State Fiscal Spending	0.23*	0.01
Federal Government Policy		
FFR Change Over Recession	0.10*	0.26*
Net Fiscal Spending Over Recession	0.14*	-0.34*

Table 5: Robustness Results - The Unemployment Rate. The table shows the marginal probability of inclusion (the posterior probability that the covariate should be included in the model) and the model probability weighted mean (eq. (11)) of the coefficients for the model given by eq. (4) estimated with recessions and recoveries defined by the unemployment rate. Covariates are listed in Table 2. State characteristics and economic conditions are included but the coefficients are not reported here. Bold 1 indicates the model inclusion probability is set to 1. * Indicates that the Marginal Probability of Inclusion exceeds 20% and the 90% Posterior Coverage interval excludes zero.

	Baseline	**Wu-Xia Shadow Rate**	**Baseline Pre-2008**	**Romer-Romer Tax, Pre-2008**	**Nakamura-Steinsson Fiscal Shocks**	**Great Rec. State ARRA Spending**
Covariate	Model Prob. Weighted Mean	Model Prob. Weighted Mean	Model Prob. Weighted Mean	Model Prob. Weighted Mean	Model Prob. Weighted Mean	Model Prob. Weighted Mean
Policy						
State Government Policy						
Budget Stabilization Fund Withdrawal Rule	-0.03	-0.02	-0.17*	-0.11*	-0.12*	-0.04
State Fiscal Spending	0.23*	0.23*	-0.02	0.10*	0.06*	0.23*
Federal Government Policy						
FFR Change Over Rec.	0.10*		0.08	0.14*	0.10*	0.09*
Wu-Xia Shadow Rate Change Over Rec.		0.09*				
Net Fiscal Spending Over Recession	0.14*	0.15*	-0.25*			0.12*
Romer and Romer Tax Shocks				0.16*		
Nakamura-Steinsson Military Spending					-0.16*	
Great Recession State ARRA Spending						-0.14*

Table 6: Robustness Results - Alternative Policy Measures. The table shows the marginal probability of inclusion (the posterior probability that the covariate should be included in the model) and the model probability weighted mean (eq. (11)) of the coefficients for the model given by eq. (4) estimated with recessions and recoveries defined by the employment. Covariates are defined in Table 2. State characteristics and economic conditions are included but the coefficients are not reported here. * Indicates that the Marginal Probability of Inclusion exceeds 20% and the 90% Posterior Coverage interval excludes zero.

Marginal Effects: Policy Robustness

Recession Length		Mean	Long	Short	Long	Short	Long	Short
Policy Conditions		Mean	Mean	Mean	Accommodative		Tight	
Change in policy	**Relevant Policy Changes**	**Change in Expected Recovery Time**						
State Government Policy								
BSF Withdrawal Rule (Pre-2008)	More restrictive withdrawal rules	-3.38	-5.87	-1.94	-4.13	-1.37	-8.35	-2.76
State fiscal (Pre-2008)	10% increase in net state fiscal spending	-0.45	-0.78	-0.26	-0.55	-0.18	-1.11	-0.37
Federal Government Policy								
FFR (Pre-2008)	100 basis point reduction over recessionary period	-0.50	-0.88	-0.29	-0.62	-0.20	-1.25	-0.41
Federal Fiscal (Pre-2008)	10% increase in average quarterly net fiscal spending	-7.12	-12.37	-4.10	-8.70	-2.88	-17.59	-5.82
Wu-Xia Shadow Rate-Full Sample	100 basis point reduction over recessionary period	-0.78	-1.44	-0.42	-1.93	-0.56	-1.08	-0.32
Romer-Romer Tax	Tax cut equal to 10% of GDP	-6.13	-10.51	-3.58	-11.82	-4.02	-9.34	-3.18
Nakamura-Steinsson	0.1% increase in targeted military spending	-0.79	-1.33	-0.47	-1.09	-0.39	-1.61	-0.57
State ARRA Spending	$10 billion in ARRA funding	-4.90	-9.03	-2.66	-11.71	-3.44	-6.96	-2.05

Table 7: Marginal Effects - Robustness Tests. The table shows the change in the expected duration of recovery time (in months) for the estimated model in eq. (4) when changing one of the four policy variables. Because the model is nonlinear, we show a number of scenarios reflecting differences in initial conditions. For all scenarios, state characteristics, S&P variables, and the number of other states in recession are set at their means (see Table 2) and max oil is set to zero. Recession lengths are set to mean, 1 std above (long), and 1 std below (short). "Policy Conditions" indicates the values of the policy variables: mean, accommodative (1 std above the mean for state and federal fiscal spending, 1 std below the mean FFR), or contractionary (1 std below the mean for state and federal fiscal spending, 1 std above the mean FFR). Except when explicitly stated, the BSF variable is set to zero. The first four rows show the change in expected duration of recovery for (1) an increased restrictiveness in the BSF withdrawal rule, (2) a 10% increase in state fiscal spending, (3) a 100-basis-point reduction in the FFR, and (4) a 10% increase in federal fiscal spending from the initial conditions indicated by "Policy Conditions" when the sample is restricted to 1978 through 2007. The last four rows row show the effect on the expected duration of recovery time of (1) a 100-basis-point decrease in the Wu-Xia shadow rate replacing the FFR for the sample 1978 to 2012; (2) a tax cut equal to 10% of GDP based on the Romer-Romer narrative tax series for the sample 1978 through 2007; (3) a 0.1% increase in targeted military spending on the state for the sample 1978 through 2006; and (4) a $10 billion increase in ARRA funding to the state for the sample 1978 through 2012.

A The Sampler

Let τ_{nt} represent the number of months for employment in state $n = 1, ..., N$ to return to its pre-recession level subsequent to a trough occurring at time t and let C_{nt} represent the number of months between state n's trough occurring at time t and its next recession occurring at time $t + C_{nt}$. We can define an indicator δ_{nt} such that $\delta_{nt} = 1$ if the end of the spell is observed (i.e., if $\tau_{nt} \leq C_{nt}$) and $\delta_{nt} = 0$ if the observation is the end of the recovery is not observed because another recessions occurred (i.e., τ_{nt} is right-censored). The censored observations do have information, because we know that the recovery lasted at least to $t + C_{nt}$. Thus, $Y_{nt} = \min\{\tau_{nt}, C_{nt}\}$ reflects the *observed component* of the recovery associated with state n's period t trough.

Let $\boldsymbol{\Upsilon} = \{\mathbf{Y}, \boldsymbol{\delta}, \mathbf{X}\}$ represent the complete data, where $\mathbf{Y}$ is the vector of observed component of the recovery for each state-recession experience, $\boldsymbol{\delta}$ is the vector of censoring indicators, and $\mathbf{X}$ is the full set of covariate data for all state-recession experiences, including the state-level fixed effects.

Let $\boldsymbol{\Theta} = \left\{\beta, \sigma^2, m\right\}$ represent the full set of model parameters, where $\beta = \left[\beta_0, \beta_x', \beta_{s,n}'\right]'$. For any Gibbs iteration, we obtain a draw (or retain the past value) of $\boldsymbol{\Theta}$ and draw the censored values of $\boldsymbol{\tau}$. We do not need to draw β, and σ^2 at every iteration since they are integrated out of the model likelihood; we only update these draws when the proposed model is accepted. However, the model indicators m and the censored elements of $\boldsymbol{\tau}$ are iteratively drawn in the MCMC algorithm.

A.1 Priors and Likelihood

Assuming a normal distribution for ε_{nt}, $\varepsilon_{nt} \overset{iid}{\sim} N\left(0, \sigma^2\right)$, implies the log-normal distribution for τ_{nt}. The complete set of augmented data, conditional on the covariates and draws of model parameters, are normally distributed, $\tau \mid X, \beta, \sigma^2 \sim N\left(\mathbf{X}\beta, \sigma^2\mathbf{I}\right)$. We assume conjugate priors for β and σ^2, which simplifies the sampler by allowing us to integrate out β and σ^2 and avoid updating the M-vector of coefficients at every iteration. Conjugate priors for this model take the following form:

$$\beta \mid \sigma^2 \sim N\left(b_0, \sigma^2 B_0\right), \tag{5}$$

$$\sigma^2 \sim IG\left(\frac{v_0}{2}, \frac{v_0\sigma_0^2}{2}\right). \tag{6}$$

Sha, Tadesse, and Vannucci (2006) explain that after integrating out β and σ^2 , the marginal likelihood of the augmented data can be expressed as

$$\mathcal{L}(\boldsymbol{\tau} \mid \mathbf{X}) \propto \left\{v_0\sigma_0^2 + (\boldsymbol{\tau} - \mathbf{X}b_0)' \left(I + \mathbf{X}B_0'\mathbf{X}'\right)^{-1} (\boldsymbol{\tau} - \mathbf{X}b_0)\right\}^{-\frac{n+v_0}{2}}, \tag{7}$$

which implies a multivariate t-distribution for the augmented data:

$$\boldsymbol{\tau} \mid \mathbf{X} \sim t_{v_0}\left(\mathbf{X}b_0, \sigma^2\left(I + \mathbf{X}B_0'\mathbf{X}'\right)\right), \tag{8}$$

where the full conditional distribution of the censored observations is a truncated t-distribution to which standard Gibbs sampling updates can be applied.

Relatively diffuse priors are assigned by setting $b_0 = 0_{M\times 1}$, and $B_0 = diag\,(h)$ with h an $M \times 1$ vector of large values. Finally, we assign a small value for v_0 to impose a weakly informative prior on σ^2.

A.2 Variable Selection

The draw of the model inclusion indicators is a form of Gibbs variable selection, which is executed using a reversible jump MCMC variable selection algorithm based upon that of Green (1995). The reversible jump step is necessary because the dimension of the model may change size across iterations of the sampler. The MCMC algorithm begins with an initial model composed of a randomly selected subset of the covariates and migrates toward models with higher posterior probability. Following the approach of Sha, Tadesse, and Vannucci (2006), we assume that when the model indicator suggests a variable be included in the model, the regression coefficients are normal; otherwise they are set to zero:

$$\beta_i|m_i \sim \begin{cases} N\left(b_{0i}, \sigma^2 B_{0i}\right) & \text{if } m_i^* = 1 \\ \delta\left(0\right) & \text{if } m_i^* = 0 \end{cases} \quad \text{for } i = 2, .., M, \tag{9}$$

where b_{0i} is the i-th element of the b_0 vector, B_{0i} is the i-th diagonal element of the B_0 matrix from (5), and $\delta\,(0)$ is a point mass density at zero. The index i excludes the first element, as this references the intercept term and is included in every proposed model. We assume a Bernoulli(p)

prior distribution for each element of the model indicators:

$$m_i \sim Bernoulli\,(p)\,.$$

We select p to differentiate how likely each of the covariates is to be included or excluded from the model: Setting $p = 0.5$ makes it equally likely for each covariate to be either included or excluded, making the prior on inclusion flat—all models are equally likely. A more restrictive prior would set $p \approx 0$, accepting only those covariates that have very strong explanatory power for the length of recoveries.

A.2.1 Generating m conditional on $\boldsymbol{\Upsilon}, \boldsymbol{\Theta}_{-m}$

The MCMC iterations alternate between updating the model indicators and updating the draws for censored recovery times. To propose a new model in the first step, we use a Metropolis algorithm to add a covariate, delete a covariate, or swap between one included and one excluded covariate. We randomly select from three potential moves:

1. Randomly choose a variable index and change it from 0 to 1 or 1 to 0.

   (a) If only one covariate is currently included, the probability of the proposed model is $\frac{M-1}{M}$, to reflect the random selection among the $M-1$ potential unused covariates.

   (b) Otherwise, the probability of the proposed model is 1.

2. Randomly exchange 0 for 1 by choosing one variable currently included and one variable currently excluded - set the probability of the proposed model again to 1.

3. Randomly select one of the covariates and swap it with the covariate either to its right or left, each with probability $p\,(m^*, m) = 0.5$ if the selection is in the interior of the list of M possible covariates. Otherwise, the probability is determined by the following criteria:

   (a) If we randomly select the first covariate, we can exchange it with the second covariate (as long as both were not already included) and give the model probability $p\,(m^*, m) = 0.5$.

(b) If we randomly select the last covariate, we can exchange it with the second-to-last covariate (again assuming both weren't already included) giving the model probability $p(m^*, m) = 0.5$.

(c) If the selection is in the interior of the list of M possible covariates, we randomly select a value u from the Uniform distribution over the interval $[0, 1]$. If $u < 0.5$ and the covariate to the left has a different indicator, exchange the selected covariate for that to its left. If $u > 0.5$, and the covariate to the right has a different indicator, exchange between those two instead. In each of these cases, set the probability of the proposed model to $p(m^*, m) = 1$.

Finally, after constructing the new model proposal m^*, the candidates m^* and β^* are accepted with probability

$$\alpha = \min\left\{1, \frac{\pi(m^* \mid \boldsymbol{\Upsilon})}{\pi(m \mid \boldsymbol{\Upsilon})} \frac{p(m, m^*)}{p(m^*, m)}\right\}, \tag{10}$$

where $\pi(m \mid \boldsymbol{\Upsilon}) \propto \pi(\mathbf{T} \mid \mathbf{X}, \boldsymbol{\delta}, m)\, \pi(m)$. The first term is the ratio of the model likelihoods. The second term is the ratio of the prior probabilities of the model indicators. A priori, we assume that each covariate is equally likely of being included in the model, and thus, each element m_i of m is assumed to be independently distributed from a Bernoulli distribution with probability 0.5. This step generates a series of observations of model indicators m that establishes the posterior probability of inclusion for each x_i covariate. In this manner, we randomly move through the model space and accept proposed models that generate a greater likelihood. We draw new values for β^* from the conditional posterior described subsequently by equation (**??**) in Section 3.3 only when accepting the proposed model m^*. The intercept term β_0 is included in every proposal so the variation in β^* comes from different combinations of covariates included and excluded in the proposed model.

The variable selection algorithm returns the marginal posterior probability of each model specification visited throughout the process. Each unique model includes a different subset of covariates and thus generates a different posterior likelihood. We use this metric to assess the added value from including or excluding covariates rather than simply looking at the covariates individually. Model selection provides a more comprehensive look at the ability of the overall model, controlling for a variety of factors, to describe recoveries.

In the second MCMC step, we update the censored elements of $\boldsymbol{\tau}$ where $\delta_{nt} = 0$ by drawing from the t-distribution of (8).

A.2.2 Selection of Relevant Variables

The marginal posterior probability that variable i be included in the model is estimated by the empirical frequency of $m_i = 1$ within the MCMC output. We will focus on those variables identified as having marginal posterior probability greater than some threshold κ: $\widehat{m}_i = I\left\{p\left(m_j = 1 \mid \mathbf{X}\right) > \kappa\right\}$.[23] In addition to this, the MCMC draws for the complete set of model indicators m generate a joint posterior distribution of covariates included in each model specification. These results allude to inference about variable selection based upon the most likely model:

$$m = \arg\max\left\{\pi\left(m^{(g)} \mid \boldsymbol{\Upsilon}\right)\right\}, \tag{11}$$

for $g = 1, ..., G$ MCMC iterations.

[23] We set $\kappa = 0.5$ as an initial threshold but allow for flexibility with covariates suggesting marginal probabilities of inclusion around 0.5.