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The Impact of Research and Development on Economic Growth and Productivity in the U.S. States: Online Appendix

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Online Appendix

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This online appendix accompanies the article forthcoming in the *Southern Economic Journal*. This appendix contains additional information on the data and methodology used in the article, as well as results from additional and supplementary estimations.

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Appendix 1: Data Description

This appendix provides more detail on the data used for the paper. Our sample includes data from 50 states and the District of Colombia between 1963 and 2007.

Macroeconomic Data

We obtained real Gross Domestic Product (GDP) for private industry by state,[1] which we refer to as State Gross Domestic Product (SGDP), from the Bureau of Economic Analysis (BEA, 2013a).[2] The units are millions of 2005 dollars.

We use Garofalo's and Yamarik (2002) state-level panel dataset for the private capital stocks.[3] Our measurement of the labor force is employment in the private sector, which is the sum of farm employment and private nonfarm employment. We obtained these data for the period 1969 to 2007 from the BEA (2013b).[4] For the six missing years of data before 1969, we constructed analogous figures for private industry employment based on the BEA's methodology.[5]

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For the human capital stock, we use the average years of schooling in the labor force. Average educational attainment is the most commonly used measure of human capital in the literature (Benhabib and Spiegel, 1994; Frantzen, 2000; Bronzini and Piselli, 2009; int. al.). We use data constructed by Turner et al. (2006), which covers the years 1963 to 2000. We supplemented this series with data from the US Census Bureau's Current Population Survey (CPS) to extend coverage to 2007,[6] resulting in a blended measure of human capital by state, 1963-2007. Unlike our other variables, which are for private industry, of necessity our measure of human capital includes the education of government workers.

The labor and capital shares of GDP in the private sector are needed to calculate TFP. Labor and capital shares of GDP are computed following Gomme and Rupert (2004). In particular, labor's share of GDP in a state is found as the ratio of unambiguous labor income (UL) to the sum of UL and unambiguous capital income (UK) (both restricted to the private sector). UL is compensation of employees and UK accounts for corporate profits, rental income, net interest income, and depreciation in the state. To smooth the resulting UL series, a three-year moving average is taken.[7] The labor and capital shares are needed only when TFP is the dependent variable in the regressions; in most of our regressions the dependent variable is SGDP.

R&D Data

We use total R&D expenditure performed by private industry, which was obtained by state from the National Science Foundation's Industrial R&D Information System (IRIS) (NSF, 2013).[8] These data are from a stratified random sample survey, the Survey of Industrial Research and Development, and thus are subject to sampling as well as measurement error, but the survey is designed to include large performers of R&D with certainty.[9] There were missing observations for some states and years for two reasons. In 18 out of the 45 years of our sample, the NSF collected no data.[10] In other cases, the data are not reported if one firm did most of the R&D in the state that year. We log-linearly impute missing values, but only if they are missing for no more than three consecutive years. Before imputation, 1,441 observations on R&D expenditure out of 2,295 year-state cells (51 states × 45 years) are available from NSF. We impute 495 values, leaving 359 observations missing after imputation. The R&D expenditure is converted from nominal to real 2005 dollars with the BEA's aggregate output price index for R&D investment.[11] Table A.11 presents the average of R&D expenditure as percentage of GDP for our sample.

To construct the R&D capital stock variable, we follow the perpetual inventory method used throughout the literature. Specifically, we estimate initial R&D capital stock with the formula $I_0/(g + \delta)$, where I_0 is the average investment of the first 3 years available, g is the average geometric growth rate of the level of investment in each series, and δ is the depreciation rate.[12] Following Coe and Helpman (1995) and Bronzini and Piselli (2009), we use a 5% depreciation rate for R&D.[13] The final R&D capital stock variable is available for 83.1% of the possible 2,295 state-years in the sample. States with many missing values are typically those with the smallest population.[14]

In our analysis we also consider the spillover effect of R&D across states. To estimate the spillover effect, we create three measures of R&D performed in other states. All take the general form of a weighted average: $RD\_OTHER_{it} = \sum_{j \neq i} w_{ij} RD_{jt}$; the difference is in the definition of the weights w_{ij}, although in all cases the weights sum to unity for each i. First, we computed a distance-weighted (i.e., spatially lagged) measure, $RD\_OTHER_{it}^{D}$. In this approach we assume that an R&D dollar spent in more distant states has less of a spillover than does R&D performed in adjacent states. Weights w_{ij} are the inverse distances between state population centroids from US Census Bureau (2000). Thus, $RD\_OTHER_{it}^{D}$ is average domestic R&D performed outside the state, where the average is computed with spatial lags. As stated above, R&D data has many missing values. To overcome this difficulty, we rescale the weights for each year and states as necessary. Rescaling the weights restores the correct magnitude to the weighted average, but does not fully get around the measurement error in out-of-state R&D created by the missing data.

To introduce the notion of distance in economic geography, in our second definition of the average other-state R&D stock, $RD\_OTHER_{it}^{S}$, we weight R&D in other states based on economic similarity and relevance of R&D across sectors (i.e., technological similarity). To construct this indicator, we calculated pairwise economic similarity weights S_{ij}^{GDP} for every pair of states *i* and *j* in our study. This is done on a year-by-year basis, although time subscripts are suppressed in the notation. The approach we take to create the economic similarity weight is the following. Let s_k^j be the share of state *j*'s economy in industry (group) *k*, measured as a fraction of SGDP. The industry groups are defined by SIC for earlier years and NAICS for later years, and are at the two- and three-digit level.[15] Then an initial similarity measure between states *i* and *j* is:

$$Q_{ij}^{GDP} = \sum_k min\{s_k^i s_k^j\} \tag{A1.1}$$

Q_{ij}^{GDP} is between zero and one, with the extremes meaning no overlap and full overlap (i.e., exactly matching proportions of industries in the composition of the two states' economies). We next refine Q_{ij}^{GDP} to control for the amount of R&D that each industry does. For example, the industrial sectors of two states may match closely but in low-R&D performing industries such as the service sector. The R&D stocks in each state will be of less relevance to the other state than if the closely matching economies were heavily skewed toward R&D-important industries such as high-tech manufacturing. Define weight S_k^{RD} to be the national-level industry weight based on how much of national total private R&D is performed in an industry *k*. Then the final similarity measure is:

$$S_{ij}^{GDP} = \sum_k S_k^{RD} min\{s_k^i s_k^j\} \qquad \text{(A1.2)}$$

While in theory S_{ij}^{GDP} ranges from zero to one, in our data the range is . From the similarity measure, weights w_{ij} are created proportional to S_{ij}^{GDP} but normalized to unity for each state *i*. Then RD_Other_{it} is defined as above: $\sum_{j \neq \mathrm{i}} w_{ij} RD_{jt}$.

For the third definition of R&D performed in other states, $RD\_OTHER_{it}^{C}$, at the suggestion of a referee we explored an alternative notion of geographic distance: contiguity. In this case the weights come from a contiguity matrix in which w_{ij} is 1 for contiguous states *i* and *j*, and zero otherwise. Again, the weights are normalized to sum to unity for each state.

Appendix 2: Methodology

Model

For the derivation of the empirical model we use to estimate the impact of R&D on output and productivity, we follow much of the empirical growth literature (e.g., Coe and Helpman, 1995; Bronzini and Piselli, 2009) and assume a production function with Hicks-neutral TFP:

$$Y_{it} = TFP_{it} {L_{it}}^{\alpha} {K_{it}}^{\beta} \tag{A2.1}$$

where *i* is a state index, and *t* is a year index. *Y* represents private sector output, *L* is private sector labor, *K* is the private sector physical capital stock; and *TFP* is Total Factor Productivity. We do not include in the production function the stock of public infrastructure, as Bronzini and Piselli (2009) do. In the case of the United States, we expect public infrastructure to be relatively homogenous across states, and we are unlikely to observe significant variation. Thus, we do not find necessary to include this variable in our estimation of the model. TFP is driven by technological change, which in turn is driven by R&D investment, human capital accumulation, and other factors. Therefore we have that

$$TFP_{it} = A_{it} {HC_{it}}^{\gamma} {RD_{it}}^{\delta} {RD\_OTHER_{it}}^{\pi} \tag{A2.2}$$

where A_{it} is the "unexplained" technical change, HC_{it} is the human capital stock, and RD_{it} is the stock of R&D capital, all for state *i* in year *t*. We follow Bronzini and Piselli (2009) and include the spillover effect of R&D across states through *RD_OTHER*, the distance-weighted R&D stock from other states. We parameterize unexplained technological change as the product of state- and year-specific fixed effects: $A_{it} = \exp(\lambda_i + \tau_t)$. Substituting this expression for A_{it} into Equation (A2.2), substituting the result into Equation (A2.1), and finally taking logs, we get:

$$y_{it} = (\lambda_i + \tau_t) + \gamma hc_{it} + \delta RD_{it} + \pi RD\_OTHER_{it} + \alpha l_{it} + \beta k_{it} + \varepsilon_{it} \quad \text{(A2.3)}$$

$$tfp_{it} = (\lambda_i + \tau_t) + \gamma hc_{it} + \delta RD_{it} + \pi RD\_OTHER_{it} + \eta_{it} \quad \text{(A2.4)}$$

where the lower-case letters stand for natural logarithm, and ε_{it} and η_{it} are error terms. To account for the year effects τ_t, we time-demean all variables (without explicitly changing our notation) from here on except where noted.

We adopt alternate assumptions about α and β for purposes of comparison. In our first econometric approach, in which log *SGDP* is the dependent variable (Equation (A2.3)), we make no assumptions about returns to scale and place no restrictions on α and β. The second approach is based on Equation (A2.4). TFP is calculated for the dependent variable as

$$TFP_{it} = Y_{it}/({L_{it}}^{\alpha}{K_{it}}^{\beta}),$$

where α and β are calculated directly from input shares in the SGDP accounts. This second method thus imposes constant returns to private inputs labor and capital, so that β = 1-α.

Econometric Strategy

We estimate the models in Equations (A2.3) and (A2.4) using our unbalanced panel with all available data between 1963 and 2007. The equations are in log levels instead of log changes in order to assess the long-run relationships in the data. The levels of output, TFP, and the R&D stock also have the advantage of being much less sensitive to measurement error than their growth rates, which can bias estimation (Griliches and Hausman, 1986). However, such trending time series are likely to be integrated, and so we use estimation techniques appropriate for integrated and cointegrated data. Based on the likely cointegration of the data, we estimate the parameters of the long-run relationships in Equations (A2.3) and (A2.4) using the Dynamic Ordinary Least Squares (DOLS) and the Pooled Mean Group (PMG) estimators. To enable unbiased estimation of the long-run relationships, in empirical application we also want to model flexibly the short-run dynamics. Below we provide an econometric model incorporating short-run dynamics, long-run relationships, and heterogeneity across panels that leads to the DOLS and PMG estimators.

Begin with the autoregressive distributed lag (ARDL) form of Pesaran et al. (1999), denoted ARDL(p,q,q,…,q):

$$y_{it} = \sum_{j=1}^{p} \lambda_{ij} y_{i,t-j} + \sum_{j=0}^{q} \delta_{ij} x_{i,t-j} + \alpha_i + \varepsilon_{it} \qquad \text{(A2.5)}$$

where x_{it} is a vector of the regressors from Equation (A2.3) (or Equation (A2.4), depending on which specification is being estimated), α_i is a fixed effect, and ε_{it} is white noise. The specification allows state-specific coefficients on the lagged dependent variable and regressors, allowing for dynamics that differ across units of the panel.

Before estimating the unrestricted form of Equation (A2.5), we first restrict $p = q = 0$ and furthermore assume y and x are each $I(1)$ and are cointegrated. Then $\theta = \delta_{i0}$ is the coefficient vector describing the long run (cointegrating) relationship between y and x. Kao and Chiang (2001) show that (under certain conditions) a consistent estimate of θ, $\hat{\theta}_{DOLS}$, can be obtained from the following panel Dynamic OLS (DOLS) regression

$$y_{it} = \theta' \, x_{it} + \sum_{j=-r}^{r} C_{ij} \, \Delta \, x_{i,t+j} + \alpha_i + \nu_{it} \qquad \text{(A2.6)}$$

where the lag/lead length $r \to \infty$ as $T \to \infty$. The DOLS model is restrictive because it requires all variables be $I(1)$, y and x to be cointegrated, and the variance structure and short run dynamics to be identical across states. Thus we use the DOLS model only for our initial estimations.

Now return to the unrestricted Equation (A2.5). Allow vector x to be I(0) or I(1), and assume that the order of integration of y is no more than the order of x. However, we still assume the long run relationship between y and x (captured by θ) is common across states. Then, we can re-write Equation (A2.5) in error correction form:

$$\Delta y_{it} = \phi_i(y_{i,t-1} - \theta' x_{it}) + \sum_{j=1}^{p-1} \lambda_{ij}^* \Delta y_{i,t-j} + \sum_{j=0}^{q-1} \delta_{ij}^* \Delta x_{i,t-j} + \alpha_i + \varepsilon_{it} \qquad \text{(A2.7)}$$

where θ and the starred coefficients are functions of the original parameters in Equation (A2.5).[16] Note that θ is again the long run relationship of interest. The short run dynamics of the dependent variable are governed by the deviation from the equilibrium long-run relationship. Parameter ϕ_i, which governs the speed of adjustment to the long run relationship, varies across states and must be between zero and -2 for the existence of a long run relationship between the dependent variable and the control variables. Under the assumptions of Pesaran et al. (1999), we have $y_{it} = \theta' x_{it} + \eta_{it}$, where for each i, η_{it} is stationary.[17]

For the reasons described in the main text, we use the Pooled Mean Group (PMG) estimator developed by Pesaran et al. (1999) for most estimations.[18] The estimations are performed using the xtpmg add-on command (Blackburne and Frank, 2007) in Stata 13.1. Testing shows that a dynamic specification of the form ARDL(1,1,1,1,1,1) is appropriate.[19]

Appendix 3: Additional Results

Tests for Nonstationarity and Order of Integration

The DOLS estimator requires that all the variables be I(1), while the PMG estimator requires that the variables be I(1) or I(0), with the order of *y* no greater than the order of the regressors. To test these assumptions, in Table A.2 we shows the results of two different unit roots tests for the variables included in our baseline model. There are many tests for panel unit roots available; we choose two that are appropriate for large *N*, large *T* asymptotics and allow unbalanced panels. The unit root test of Im et al. (2003) has the null hypothesis that all panels are integrated and the alternative hypothesis that at least one panel is stationary. [20] The results for the variables before removing the time-means are in the first column of Table A.2, and they show that the human capital variable may not have unit roots in each state. The conclusions are the same from the ADF-Fisher tests (Choi, 2001). [21] We next test the time-demeaned variables; results are in the middle pair of columns of Table A.2. We fail to reject the null hypothesis of nonstationarity for any variable except TFP at the 5% level, although the null is still rejected for human capital at the 10% level. The ADF-Fisher tests fail to reject the null hypothesis for any variable. There is thus mixed evidence for the nonstationarity of TFP. If TFP is I(0), the DOLS estimator will fail but the PMG estimator is still consistent.

To make sure none of the variables is integrated at higher orders, we repeat the tests on the differenced form of the variables (results are in the last two columns of Table A.2). The hypothesis of nonstationarity of all panels is convincingly rejected in each case. Thus, each series appears to be *I*(1) in each state, except possibly TFP. In summary, the data appear to satisfy the assumptions of the DOLS and PMG estimators when SGDP is used as the dependent variable but satisfy only the assumptions of the PMG estimator with TFP as the dependent variable.

We also explore whether there is evidence of cointegration, as supposed by our estimation strategy. To test for cointegration we use a battery of residual-based tests for panel data from Pedroni (1999) and Kao (1999). We perform the cointegration test for the SGDP and TFP models using the baseline regression specification introduced in the next section. The results are shown in Table A.3. The null hypothesis of no cointegration is rejected in the majority of cases overall, although the case is weaker for the TFP regression. The parametric panel t-statistic, which Örsal (2007) found to have the best size and power among the Pedroni statistics, rejects the null for all cases except the TFP regression with time-demeaned variables.[22] Given that failure to reject the null may merely indicate low power of a test, we interpret the mixed results as providing reasonable evidence for the existence of long-run relationships among the data, except perhaps for TFP with time-demeaned variables.

Baseline DOLS Estimation Results

Kao et al. (1999) assess the econometric validity of using OLS for cointegrated data, and propose the use of dynamic OLS (DOLS) instead to avoid bias. We thus begin (but do not conclude) our empirical exploration with DOLS. Table A.4 presents the DOLS estimates for the baseline estimations.[23] The first two estimations, for SGDP and TFP, respectively, use the raw data without removing the time means. The third DOLS estimation in Table A.4 is for SGDP and uses the time-demeaned data. Regardless of which DOLS estimation is considered, we find that there is evidence of a positive effect of R&D on SGDP in the long run from R&D performed in the state. The long-run own-elasticity for R&D varies from 0.013 to 0.061 among the estimations. These elasticities fall within the range of results for R&D own-elasticity estimates from country-level panel data studies cited in Hall et al. (2010).

The results for the impact from other-state R&D are mixed when using the DOLS estimator. In the first estimation, the other-elasticity is 0.050 and highly significant. The second estimate is about the same magnitude but insignificant. Recall that the dependent variable in this regression, TFP, may not be integrated within each state, which would lead to inconsistency in the DOLS estimates. The third estimate, from the time-demeaned data, is negative, a puzzling result. There are some other unexpected results that may indicate that the assumptions of the DOLS model are not satisfied. While capital and labor contribute positively and significantly to SGDP, the coefficient on capital is larger than (in column 1) or equal to (in column 3) the coefficient on labor.[24] Furthermore, human capital is not statistically significant in the first estimation, which is unexpected given the great importance this variable has been found to have in other growth and TFP regressions (Mankiw et al., 1992; Coe et al,, 2009; Bronzini and Piselli, 2009). The insignificance of human capital in the cointegrating relationship may be related to the evidence presented above that human capital may not in fact have a unit root in all panels before time-demeaning the variable.[25] The varied performance of the DOLS approach leads us to focus our analysis on the less restricted PMG estimator.

Baseline PMG Estimations

The results for the main PMG estimations are found in the main text. Additionally, Table A.5 here reports the short-run coefficients omitted from Table 2 in the main text. As notes in the main text, there are no significant short-run impacts of R&D on growth or TFP (apart from the short-run coefficient on ΔRD_OTHER^S in column (3)). Given our focus on the long-run impacts of R&D, we do not discuss the short-run results further.

PMG with Contiguity-Weighted Other States' R&D Stock

In the main text, we refer to an estimation in which the contiguity-weighted measure of the other-state R&D stock (*RD_OTHER*^{C}) is used as a regressor instead of the distance-weighted measure *RD_OTHER*^{D}. The results are in column (4) of Table A.4 (for the long-run coefficients) and column (5) of Table A.5 (for the short-run coefficients). The results are qualitatively similar to the results from the main estimation: own- and other-state R&D still have positive, highly statistically significant effects on SGDP. Compared to the main estimation results using *RD_OTHER*^{D}, the own-R&D elasticity is somewhat higher and the other-state R&D elasticity is much lower. The latter results is not surprising, given that spatial weighting based on contiguity ignores the presence of most R&D done elsewhere in the nation. R&D performed in non-contiguous states is therefore an omitted variable, which can bias the estimates for the impact of *RD_OTHER*.

Marginal Returns to R&D Investment by State

Table 3 in the main text shows the marginal returns to R&D, the spillover ratio, and the spillover fraction for the various main estimations, where all figures are averaged over states. Table A.6 included here shows the state-by-state results for two of the main PMG estimations. Alaska and Hawaii are estimated to see less than 10% of total returns spill over to other states, while more than 90% of total returns leave the borders of Connecticut, Delaware, Idaho, Michigan, New Jersey, and New Mexico. Differences in the returns and spillovers across states come from differences in the spatial weights and the SGDP to R&D stock ratios of the states. Recall from a footnote in the main text that the marginal impact of own R&D is calculated as $\delta \sum_i a_i r_i$, where δ is the own-elasticity for R&D, $a_i = \bar{Y}_i / \sum_j \bar{Y}_j$ is the cross-state GDP weight, $r_i = \sum_t b_{it} Y_{it} / RD_{it}$ is the average output to R&D ratio in the state, and $b_{it} = Y_{it} / \sum_s Y_{is}$ is the within-state GDP weight. Thus, due to r_i in the formulas, states with *high* R&D to SGDP ratios will, ceteris paribus, have *lower* marginal returns. We see this with California and Washington state, for example; both have low marginal returns compared to other states. The opposite is also true: states with low R&D/SGDP ratios, such as Alaska, South Dakota, and Wyoming, tend to have much higher calculated marginal returns. These results are in accord with the notion that there are decreasing returns to R&D activity performed at any one point in time.

Testing the Residuals for Autocorrelation

Consistency of the PMG estimates requires that the error terms in equation (A2.3) from the main text be white noise. In this section we test the residuals from the main baseline estimation (from column (1) of Table 2 in the main text) for autocorrelation. The first test statistic we compute is the Durbin-Watson (D-W) *d* statistic.[26] As is so often the case with D-W testing, the *d* statistic falls into the inconclusive region between DL and DU (the upper and lower critical values) for most states. However, in *no* case do we conclusively reject the null hypothesis of no first-order positive serial autocorrelation, and in four cases we conclusively fail to reject the null hypothesis. There is thus no apparent evidence against the hypothesis of white noise from this test.

The next test is *portmanteau* test (or *q*) test of Box and Pierce (1970) as refined by Ljung and Box (1978). The null hypothesis of the test is that the regression residuals are white noise. We calculate four versions of the test statistic, with an increasing number of autocorrelations included in the test. Of the 204 test statistics calculated, 10 have *p*-values less than 0.05, and only two have *p*-values less than 0.01. Seven of the 10 statistics with *p*-values less than 0.05 come from two states, Arkansas and Utah, and so we subject data from those states to greater scrutiny (even though Arkansas was one of the few states for which the D-W test conclusively failed to reject the hypothesis of serial correlation). Setting those two states aside for the moment, with this many test statistics the fact that there are three remaining with *p*-values less than 0.05 does not concern us. A back of the envelope calculation shows that the probability of observing three or more Type I errors (false rejections) with a 5% test and this many test statistics is 99.7%.[27] Thus we expect that these rejections are nothing more than Type I errors.[28]

Returning now the possibility of serial correlation in the residuals for Arkansas and Utah, we next re-estimated the baseline specification allow an additional lag each for the dependent variable and the other regressors. This raises the ARDL lag lengths to $p = q = 2$ (refer to equation (3) in the main text), but only for those two states. This yields the estimation reported in column (4) of Table 4 in the main text; refer thence for discussion. After estimation of the augmented regression we re-tested the residuals. Since the regression now includes a lagged dependent variable as a regressor for those two states, we replace the D-W statistic with Durbin's *h* statistic (refer to footnote 26), which is asymptotically valid for this situation. The p-values for the tests for these two states are 0.521 and 0.146, and we do not reject the hypothesis that there is no serial correlation. The eight *q*-statistics for these two states all have *p*-values above 0.05. We thus conclude that even if the main baseline specification did suffer from autocorrelation in the residuals—for which the evidence is mixed—the augmented regression does not. Table A.7 provides the Durbin-Watson d statistic and the Pormanteau Q-statistic p-values for lags 1-4 for each state.

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Endnotes

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[1] The real GDP by state series from BEA are not available before 1987, and the chained indexes by state series are not available before 1977. Therefore we used the US GDP implicit price deflator (from NIPA table 1.1.9, with change of basis from 2009 to 2005) for the US and applied it to the nominal state GDP series.

[2] The BEA changed its methodology in the state product accounts in 1997, switching from the SIC to the NAICS for classification of industry. Given that we do not break GDP down by industry, we ignore this change.

[3] We use their Net Private Capital Stock created for 1-digit SIC and NAICS industries. We also converted the basis of the series from 2000 to millions of chained 2005 dollars.

[4] Our labor force data comes from BEA Tables SA25 and SA25N, Total Full-Time and Part-Time Employment by Industry.

[5] We calculate employment in private industry from 1963 to 1968 from various available but inconsistent sources in the following way. First, we collected government employment (GE) from the Statistical Abstracts of the US for each year (GE_SA_t). These data do not match the figures available from BEA from 1969 on, but we assume that the implied growth rate in GE is correct. Therefore, using 1969 as the reference year, we use the data from the Statistical Abstracts to calculate a government employment (GE) index series ($GEI_t = GE\_SA_t/GE\_SA_{1969}$) for t = 1963,…,1969. Applying the index to the GE figure from BEA (GE_BEA) for 1969 creates a synthetic series for GE during 1963-1968 ($GE_t = GE\_BEA_{1969}/GEI_t$) that blends smoothly into the BEA series in 1969. We then calculate a similar index series for total employment (TE) for the period 1963-1969 ($TEI_t = TE\_B_t/TE\_B_{1969}$), where TE_B is total employment from Turner et al. (2006) (we thank Robert Tamura for sharing these data). Applying the index to the BEA figure for total employment (TE_BEA) for 1969 creates a synthetic series for TE: $TE_t = TE\_BEA_{1969}/TEI_t$). Then we estimate private employment PE as the difference between total employment and government employment: $PE_t = TE_t - GE_t$.

[6] From each year's March supplement to the CPS, we constructed weighted estimates for each state of the number of years of education of individuals in the civilian labor force. Schooling in the CPS (variable A_HGA) is interval censored, so our calculation assumed that "grades 1 to 4" = 3 years, "grades 5-6" = 5.5 years, "grade 12 but no HS diploma" = 11.5 years, "some college but no degree" = 13 years, associate college degrees = 14 years; bachelor's degrees = 16 years; master's degrees = 18 years, professional school degrees and PhDs = 20 years. We created an index series for each state, using methodology similar to that described in note 5 for the employment statistics. The indices are used to create synthetic state-specific series that blend into the data from Turner et al. (2006) in 2000. This procedure tacitly assumes that the growth in human capital after 2000 can be accurately estimated from the CPS. Differences between the series before blending were generally small: in 2000, the overlapping year, the average difference was 1.1% with an interquartile range of 0 to 3.5%.

[7] UL is taken directly from BEA NIPA data for the private sector. UK is calculated using the national income accounting identity UK = (private sector GDP) – (private sector UL + private sector ambiguous labor income), where ambiguous labor income = taxes less subsidies + proprietor income (Gomme and Rupert, 2004). All data are from the state accounts. The three-year moving average is applied to each state's UL series before computing UK.

[8] The measure includes all expenditure on R&D performed by industry, regardless of the source of funds. Late data are from Table 60, "Funds for and companies performing industrial R&D in the United States, by state and source of funds: 1999–2007." Table H-21, "Total (company, Federal, and other) funds for industrial R&D performance, by State for selected years: 1963–98" supplies earlier years.

[9] For example, by the end of the period all companies among those known to conduct R&D in any of the previous five survey years and that spent $3 million or more on R&D were included with certainty. Details on the complex sampling scheme are in Appendix A to NSF (2011).

[10] Data are missing for even years from 1964-1996 and for 2000.

[11] The BEA R&D Satellite Account for 2010, available at http://www.bea.gov/rd/xls/1959_2007_rd_data_2010RDSA.xls, contains alternatives for indexing R&D investment. Copeland et al. (2007) describers the aggregate output price index that we use as "a second-best solution that reflects implementation challenges and data limitations" (p.4).

[12] In states with a break in the time series after imputation, the calculation of the stock variable begins anew after the break (i.e., data from before the break are not used).

[13] Hall et al. (2010) report that the empirical literature typically finds that estimates of the effects of R&D are insensitive to different depreciation rates in constructing the R&D stock.

[14] The states with missing observations for R&D stock (with the number missing, out of 45 years possible, in parentheses) are: Montana (32), North Dakota (32), Idaho (30), Alaska (24), Vermont (23), Delaware (22), South Dakota (22), New Hampshire (21), West Virginia (21), Hawaii (20), Maine (17), New Mexico (16), Oregon (16), Washington (16), Nevada (12), DC (11), Nebraska (9), Wyoming (9), Georgia (8), Virginia (8), California (7), Mississippi (7), and Kentucky (5).

[15] The industry groups were chosen to match as closely as possible the available data from NSF on R&D performed by industry.

[16] In particular, $\theta = \sum_{j=0}^{q} \delta_{ij} / (1 - \sum_{j=1}^{p} \lambda_{ij})$ and is assumed in the PMG model to be constant across i.

[17] Recall that we time-demean all variables to account for trends not otherwise explained by the model, which further ensures the stationarity of η_{it}.

[18] For more detailed description of the structure of the PMG model, refer to Pesaran et al. (1999) and Blackburne and Frank (2007).

[19] Lag length was selected based on the Schwarz Bayesian Information criterion (SBIC). We performed the test for each state in the sample and select the lag length that is appropriate in

most states (we use the mode of the lag length test from all states, which was equal to zero according to the SBIC).

[20] In this test we use a number of lags chosen by the AIC criterion in constructing the test statistic, to account for serial correlation. The test was performed using the xtunitroot ips command in Stata 13 with the “lags(aic 5)” option.

21 Instead of constructing a single test statistic, the ADF-Fisher test instead combines the p-values from separate tests on each panel into an omnibus p-value (Choi, 2001). The test was performed using the xtunitroot fisher command in Stata 13 with five lags for serial correlation.

[22] We note that the same tests that fail to reject at the 5% level in the baseline R&D regressions of Bronzini and Piselli (2009) (the panel v-, and group and panel ρ-statistics) also fail to reject here. They nevertheless concluded, as we do here, that the evidence is for the existence of long-run relationships among the data.

[23] The number of leads and lags in each DOLS estimation was selected based on the SBIC.

[24] The conventional wisdom (and much empirical evidence) holds that labor’s share of output is about twice capital’s share of output in the US economy.

[25] The DOLS estimates shown in Table A.4 are similar to results found when we use the Fully Modified Ordinary Least Squares (FMOLS). FMOLS, a competing estimator to DOLS, has been found to perform worse than DOLS when estimating cointegrated panel regressions, and we do not report the results here. See Baltagi (2008, p.299) for a discussion of the DOLS and FMOLS.

[26] The D-W test is biased if the lagged dependent variable appears as a regressor, as may appear to the reader to be the case in the ARDL specification (equation (3) in the main text). However, under the lag lengths chosen by the SBIC for the main specifications this is not the case.

[27] Assuming that the statistics are independent random variables for simplicity, the probability that zero, one, or two statistics have *p*-values less than 0.05 can be readily computed. Then subtracting the sum of the probabilities from one yields the probability that three or more tests out of the 196 will falsely reject. Further details of the calculation are available upon request.

[28] In fact, the same back of the envelope calculation shows that the probability of observing 10 false rejections out of all 204 tests is 57.1%. Nevertheless, we will not assume that the rejections are meaningless for Arkansas and Utah.

Table A.1: Average of R&D expenditure as percentage of GDP, 1963- 2007

State Code	R&D intensity	State Code	R&D intensity	State Code	R&D intensity
Alabama	1.1	Kentucky	0.5	N. Dakota	0.6
Alaska	0.1	Louisiana	0.4	Ohio	1.8
Arizona	1.9	Maine	0.5	Oklahoma	0.7
Arkansas	0.3	Maryland	1.8	Oregon	1.6
California	3.6	Massachusetts	4.0	Pennsylvania	2.2
Colorado	1.9	Michigan	4.3	Rhode Island	1.8
Connecticut	3.9	Minnesota	2.2	S. Carolina	0.8
Washington, DC	2.9	Mississippi	0.2	S. Dakota	0.3
Delaware	0.7	Missouri	1.5	Tennessee	1.1
Florida	1.1	Montana	0.3	Texas	1.3
Georgia	0.7	Nebraska	0.4	Utah	1.5
Hawaii	0.3	Nevada	0.8	Vermont	1.9
Idaho	2.8	N. Hampshire	2.3	Virginia	1.2
Illinois	1.6	New Jersey	3.7	Washington	3.8
Indiana	1.8	New Mexico	3	W. Virginia	0.8
Iowa	1.0	New York	1.6	Wisconsin	1.3
Kansas	1.2	N. Carolina	1.2	Wyoming	0.2

Source: National Science Foundation (2013).

Table A.2: P-values from panel tests for unit roots

	Variables in Levels		Time-Demeaned Variables in Levels		Time-Demeaned Variables in Differences	
	Im, Pesaran, & Shin Test	ADF-Fisher Test	Im, Pesaran, & Shin Test	ADF-Fisher Test	Im, Pesaran, & Shin Test	ADF-Fisher Test
Ln(SGDP)	1.000	1.000	0.308	0.205	0.000	0.000
Ln(TFP)	0.999	1.000	0.020	0.258	0.000	0.000
Ln(Labor force)	0.100	1.000	0.845	0.358	0.000	0.000
Ln(Physical capital)	1.000	0.959	0.866	0.919	0.000	0.000
Ln(Human capital)	0.000	0.000	0.071	0.750	0.000	0.000
Ln(R&D Stock)	1.000	1.000	0.997	0.345	0.000	0.000

Notes: Figures are *p*-values from the test stated in the column subheading, where the variable tested is given in the row heading and is in levels or differences as specified in the column superheading. The specified lags for serial correlation in the test statistics is five. The null hypothesis of each test is that each time series in the panel contains unit roots (i.e., that each states' time-series is non-stationary), while the alternative hypothesis is that at least one time series in the panel is stationary. For the ADF-Fisher test, an inverse chi-squared transformation that is suitable for large N is used to combine the *p*-values from the panels (Choi, 2001).

Table A.3: *P*-values from panel tests for cointegration

	Non-Time-Demeaned Variables		Time-Demeaned Variables	
Specification:	SGDP	TFP	SGDP	TFP
Pedroni tests				
Panel v-statistic	0.239	0.078	0.448	0.750
Panel ρ-statistic	0.942	0.934	0.949	0.997
Panel t-statistic (nonparametric)	0.000	0.547	0.008	0.997
Panel t-statistic (parametric)	0.000	0.004	0.000	0.755
Group ρ-statistic	1.000	1.000	0.996	1.000
Group t-statistic (nonparametric)	0.000	0.562	0.000	0.999
Group t-statistic (parametric)	0.000	0.000	0.000	0.006
Kao Tests				
ADF statistic	0.000	0.000	0.000	0.000
t_{ADF} statistic	0.000	0.000	0.000	0.000

Figures are the *p*-values from the regression-based hypothesis tests for no cointegration from Pedroni (1999) and Kao (1999); refer to these sources for the formulae for the test statistics. The regression specification is the baseline specification used in our analysis. Rejection of the null in favor of the alternative hypothesis of cointegration is evidence in favor of the existence of long run relationships among the regressors. Lag length selection is based on AIC; results based on SIC were nearly identical.

Table A.4: DOLS estimations and PMG estimation with contiguity-weighted other-state average R&D stock

Dependent Variable:	SGDP	TFP	SGDP	SGDP
Estimator:	DOLS	DOLS	DOLS	PMG
	(1)	(2)	(3)	(4)
Long run coefficients				
R&D Stock	0.032***	0.061***	0.013***	0.083***
	(0.006)	(0.011)	(0.005)	(0.007)
Other States' R&D Stock (RD_OTHER^D, weighted by distance)	0.050***	0.041	-0.086**	
	(0.016)	(0.027)	(0.034)	
Other States' R&D Stock (RD_OTHER^C, weighted by contiguity)				0.037***
				(0.009)
Years of Schooling	-0.009	0.843***	0.423***	1.246***
	(0.077)	(0.124)	(0.128)	(0.156)
Physical Capital Stock	0.648***		0.566***	0.423***
	(0.033)		(0.039)	(0.038)
Labor Force	0.484***		0.571***	0.615***
	(0.030)		(0.037)	(0.039)
Error Correction (ϕ_i), averaged across states				-0.162***
				(0.024)
All variables time-demeaned	No	No	Yes	Yes
State fixed effects	Yes	Yes	Yes	Yes
State-specific short-run dynamics & error variances	No	No	Yes	Yes
No. States	51	51	51	49
No. Obs.	1,615	1,762	1,619	1,789
R-squared	0.999	0.909	0.999	
Log Likelihood				4,484

***, **, and * denotes significance at 1%, 5%, and 10% level, respectively.

Figures are the long-run coefficients and standard errors (in parentheses) from pooled mean-group estimation. Figures shown for the error correction term are for the average of the state-specific estimates of ϕ_i. The short run coefficients are omitted in the table. Estimations include observations for 44 years during the period 1963-2007. Estimations include a minimum of 12 observations per state and a maximum of 44, with an average number of observations per state of 36.

Table A.5: Baseline PMG estimation results (short run coefficients)

Dependent Variable:	SGDP	TFP	SGDP	SGDP	SGDP
	(1)	(2)	(3)	(4)	(5)
Short run coefficients					
Δ R&D Stock	-0.007	-0.012	0.000	0.014	-0.014
	(0.012)	(0.023)	(0.012)	(0.014)	(0.009)
Δ Other States' R&D Stock (Δ RD_OTHER^D, weighted by distance)	-0.778	-0.951		-0.551	
	(0.472)	(0.535)		(0.307)	
Δ Other States' R&D Stock (Δ RD_OTHER^S, weighted by economic similarity)			-0.268**	0.613	
			(0.067)	(0.993)	
Interaction term, Δ(RD_OTHER^D ×RD_OTHER^S)				7.462	
				(9.039)	
Δ Other States' R&D Stock (Δ RD_OTHER^C, weighted by contiguity)					-0.106
					(0.069)
Δ Years of Schooling	-0.269*	-0.257*	-0.237	-0.258*	-0.164
	(0.111)	(0.121)	(0.125)	(0.118)	(0.108)
Δ Physical Capital Stock	0.304**		0.264**	0.305**	0.305**
	(0.033)		(0.043)	(0.042)	(0.040)
Δ Labor Force	0.621**		0.723**	0.615**	0.701**
	(0.076)		(0.106)	(0.067)	(0.078)
Constant	-0.001	0.003	-0.007	-0.006	-0.005
	(0.005)	(0.007)	(0.007)	(0.006)	(0.006)

Table notes: For the long run coefficients, number of observations, and log likelihoods from these estimations, refer to Table 2 in the main paper for columns (1) to (4). For column (5), refer to column (4) of Table A.4

Table A.6: Marginal returns to R&D investment, within state and spillovers, by state

	Estimation (1) from Table 2 in the Main Text: Distance weighted other-state R&D stock				Estimation (3) from Table 2 in the Main Text: Economic-similarity weighted other-state R&D stock			
	Within-State Marginal Return	Marginal Return Spillovers	Spillover Ratio	Spillover Fraction	Within-State Marginal Return	Marginal Return Spillovers	Spillover Ratio	Spillover Fraction
	(1)	(2)	(2) ÷ (1)	(2) ÷ [(1) + (2)]	(1)	(2)	(2) ÷ (1)	(2) ÷ [(1) + (2)]
Alabama	0.689	2.332	3.386	0.772	1.289	4.379	3.398	0.773
Alaska	9.712	0.655	0.067	0.063	18.175	1.452	0.08	0.074
Arizona	0.490	2.078	4.240	0.809	0.917	4.645	5.064	0.835
Arkansas	6.788	2.363	0.348	0.258	12.704	4.341	0.342	0.255
California	0.230	0.866	3.758	0.790	0.431	4.316	10.006	0.909
Colorado	0.473	1.860	3.935	0.797	0.885	4.399	4.972	0.833
Connecticut	0.210	2.612	12.412	0.925	0.394	5.257	13.35	0.93
Delaware	0.245	2.793	11.401	0.919	0.459	3.147	6.863	0.873
Wash., DC	1.088	3.173	2.917	0.745	2.036	1.749	0.859	0.462
Florida	0.748	1.379	1.842	0.648	1.401	3.843	2.743	0.733
GA	1.476	2.192	1.485	0.598	2.762	4.156	1.504	0.601
Hawaii	7.554	0.499	0.066	0.062	14.137	1.563	0.111	0.1

Table continued	Estimation (1) from Table 2 in the Main Text: Distance weighted other-state R&D stock				Estimation (3) from Table 2 in the Main Text: Economic-similarity weighted other-state R&D stock			
	Within-State Marginal Return	Marginal Return Spillovers	Spillover Ratio	Spillover Fraction	Within-State Marginal Return	Marginal Return Spillovers	Spillover Ratio	Spillover Fraction
	(1)	(2)	(2) ÷ (1)	(2) ÷ [(1) + (2)]	(1)	(2)	(2) ÷ (1)	(2) ÷ [(1) + (2)]
Idaho	0.167	1.818	10.905	0.916	0.312	3.766	12.067	0.923
Illinois	0.519	2.350	4.526	0.819	0.972	4.904	5.046	0.835
Indiana	0.423	2.778	6.566	0.868	0.792	5.3	6.693	0.87
Iowa	0.805	2.299	2.855	0.741	1.507	4.78	3.172	0.76
Kansas	0.909	2.214	2.435	0.709	1.702	4.585	2.695	0.729
Kentucky	1.942	2.602	1.340	0.573	3.634	4.744	1.306	0.566
Louisiana	1.358	2.054	1.512	0.602	2.542	3.226	1.269	0.559
Maine	2.609	1.599	0.613	0.380	4.882	3.718	0.762	0.432
Maryland	0.434	2.800	6.448	0.866	0.813	4.133	5.086	0.836
Massachusetts	0.211	1.957	9.274	0.903	0.395	5.156	13.055	0.929
Michigan	0.186	2.265	12.196	0.924	0.347	4.14	11.914	0.923
Minnesota	0.395	1.876	4.754	0.826	0.738	4.408	5.97	0.857
Mississippi	7.775	2.334	0.300	0.231	14.55	4.577	0.315	0.239

Table continued	Estimation (1) from Table 2 in the Main Text: Distance weighted other-state R&D stock				Estimation (3) from Table 2 in the Main Text: Economic-similarity weighted other-state R&D stock			
	Within-State Marginal Return	Marginal Return Spillovers	Spillover Ratio	Spillover Fraction	Within-State Marginal Return	Marginal Return Spillovers	Spillover Ratio	Spillover Fraction
	(1)	(2)	(2) ÷ (1)	(2) ÷ [(1) + (2)]	(1)	(2)	(2) ÷ (1)	(2) ÷ [(1) + (2)]
Missouri	0.443	2.315	5.224	0.839	0.829	5.095	6.143	0.86
Montana	2.546	1.600	0.628	0.386	4.765	1.967	0.413	0.292
Nebraska	4.431	2.097	0.473	0.321	8.292	4.436	0.535	0.349
Nevada	2.666	3.389	1.271	0.560	4.99	2.028	0.406	0.289
N. Hampshire	0.642	2.180	3.395	0.772	1.202	4.494	3.74	0.789
New Jersey	0.198	2.755	13.917	0.933	0.37	4.613	12.453	0.926
New Mexico	0.113	1.955	17.291	0.945	0.212	3.112	14.708	0.936
New York	0.385	2.242	5.831	0.854	0.72	3.952	5.491	0.846
N. Carolina	0.836	2.176	2.603	0.722	1.565	4.611	2.947	0.747
N. Dakota	2.924	1.646	0.563	0.360	5.472	2.839	0.519	0.342
Ohio	0.378	2.423	6.412	0.865	0.707	5.179	7.322	0.88
Oklahoma	0.945	2.258	2.389	0.705	1.769	4.412	2.495	0.714
Oregon	1.165	1.728	1.483	0.597	2.181	4.038	1.852	0.649
Pennsylvania	0.323	2.484	7.694	0.885	0.604	4.975	8.236	0.892

Table continued	Estimation (1) from Table 2 in the Main Text: Distance weighted other-state R&D stock				Estimation (3) from Table 2 in the Main Text: Economic-similarity weighted other-state R&D stock			
	Within-State Marginal Return	Marginal Return Spillovers	Spillover Ratio	Spillover Fraction	Within-State Marginal Return	Marginal Return Spillovers	Spillover Ratio	Spillover Fraction
	(1)	(2)	(2) ÷ (1)	(2) ÷ [(1) + (2)]	(1)	(2)	(2) ÷ (1)	(2) ÷ [(1) + (2)]
Rhode Island	0.917	2.642	2.880	0.742	1.717	4.349	2.533	0.717
S. Carolina	1.127	2.327	2.064	0.674	2.11	4.409	2.09	0.676
S. Dakota	10.417	1.891	0.182	0.154	19.496	3.247	0.167	0.143
Tennessee	0.672	2.428	3.614	0.783	1.257	4.913	3.908	0.796
Texas	0.721	1.537	2.132	0.681	1.349	4.562	3.381	0.772
Utah	0.535	2.043	3.819	0.792	1.001	4.372	4.368	0.814
Vermont	0.603	1.961	3.254	0.765	1.128	4.639	4.114	0.804
Virginia	0.804	2.347	2.918	0.745	1.505	4.44	2.949	0.747
Washington	0.265	1.394	5.258	0.840	0.496	3.584	7.223	0.878
W. Virginia	1.269	2.616	2.061	0.673	2.375	3.566	1.501	0.6
Wisconsin	0.613	2.334	3.806	0.792	1.148	4.818	4.198	0.808
Wyoming	15.199	1.857	0.122	0.109	28.443	1.87	0.066	0.062

Notes: Marginal returns in the first two columns are calculated as weighted averages: figures are calculated first at the state and year level and then are averaged across years (weighted by SGDP in the state across years). Figures in columns (1) and (2) are expressed as the one-time marginal returns to a $1 increase in the own-state R&D stock. Estimates are based on the estimated elasticities from the PMG estimation in Table 2 given in the supercolumn headings. The spillover ratio and the spillover fractions are calculated using the formula in the column heading.

Table A.7: Testing for autocorrelation by state

State	T	Durbin-Watson d statistic	Portmanteau Q-statistic (p-values)			
			1 lag	2 lags	3 lags	4 lags
Alabama	44	1.706†	0.986	0.825	0.475	0.640
Alaska	20	1.986†	0.982	0.422	0.477	0.627
Arizona	44	1.898†	0.770	0.704	0.872	0.592
Arkansas	44	2.310‡	0.184	0.040	0.026	0.035
California	37	2.230†	0.458	0.745	0.895	0.425
Colorado	44	1.825†	0.574	0.346	0.091	0.148
Connecticut	44	1.642†	0.220	0.453	0.663	0.732
Delaware	21	2.030†	0.855	0.970	0.963	0.794
Wash., DC	32	2.093†	0.710	0.920	0.762	0.503
Florida	44	1.560†	0.146	0.286	0.387	0.364
Georgia	36	1.900†	0.804	0.967	0.994	0.800
Hawaii	23	1.309†	0.464	0.150	0.281	0.425
Idaho	14	1.883†	0.840	0.035	0.057	0.064
Illinois	44	1.699†	0.318	0.424	0.625	0.556
Indiana	44	2.199†	0.370	0.576	0.443	0.464
Iowa	44	2.413‡	0.116	0.259	0.423	0.565
Kansas	44	2.311‡	0.163	0.167	0.234	0.367
Kentucky	38	2.106†	0.575	0.065	0.140	0.242
Louisiana	44	1.451†	0.076	0.118	0.194	0.315
Maine	26	1.341†	0.237	0.351	0.415	0.371
Maryland	44	2.380‡	0.152	0.163	0.270	0.387

State	T	Durbin-Watson d statistic	Portmanteau Q-statistic (p-values)			
			1 lag	2 lags	3 lags	4 lags
Massachusetts	44	1.734†	0.416	0.663	0.844	0.749
Michigan	44	1.848†	0.616	0.721	0.836	0.613
Minnesota	44	1.889†	0.795	0.904	0.618	0.463
Mississippi	36	1.831†	0.885	0.459	0.669	0.813
Missouri	44	1.812†	0.555	0.826	0.921	0.885
Montana	12	2.030†	0.792	0.922	0.982	0.672
Nebraska	35	2.188†	0.312	0.594	0.399	0.427
Nevada	31	1.222†	0.073	0.178	0.254	0.206
N. Hampshire	22	2.132†	0.162	0.106	0.148	0.251
New Jersey	44	1.768†	0.429	0.700	0.329	0.472
New Mexico	27	1.652†	0.475	0.759	0.906	0.789
New York	44	1.885†	0.736	0.185	0.328	0.486
N. Carolina	44	1.845†	0.653	0.322	0.292	0.194
N. Dakota	12	2.374†	0.258	0.427	0.358	0.421
Ohio	44	1.897†	0.731	0.752	0.901	0.853
Oklahoma	44	2.022†	0.925	0.297	0.166	0.259
Oregon	27	2.379†	0.262	0.041	0.044	0.074
Pennsylvania	44	2.185†	0.451	0.476	0.396	0.542
Rhode Island	44	1.690†	0.352	0.228	0.197	0.148
S. Carolina	44	1.624†	0.331	0.516	0.679	0.770
S. Dakota	22	1.622†	0.385	0.402	0.386	0.191
Tennessee	44	1.937†	0.878	0.533	0.722	0.844

State	T	Durbin-Watson d statistic	Portmanteau Q-statistic (p-values)			
			1 lag	2 lags	3 lags	4 lags
Texas	44	1.625†	0.202	0.434	0.522	0.669
Utah	44	1.266†	0.015	0.005	0.009	0.010
Vermont	20	1.767†	0.687	0.820	0.939	0.982
Virginia	36	2.157†	0.604	0.631	0.613	0.750
Washington	27	1.620†	0.616	0.642	0.799	0.759
W. Virginia	22	1.780†	0.900	0.221	0.368	0.527
Wisconsin	44	1.394†	0.069	0.059	0.054	0.106
Wyoming	34	2.244†	0.446	0.361	0.270	0.263

† D-W statistic is in the inconclusive region between DL and DU (the upper and lower critical values, respectively).

‡ D-W statistic is above DU and the null hypothesis of positive first-order serial correlation is not rejected.

Table notes: Testing is based on the residuals from the main baseline PMG estimation (the first estimation reported in the main text). *T* is the number of observations in the time series for the state. The *d* statistic is an asymptotic test for AR(1) serial correlation in the regression errors. The *portmanteau* test (also called a *q test*; see Box and Pierce (1970) and Ljung and Box (1978)) is for whether the residuals are white noise, and the lags noted are for the number of autocorrelations computed and included in the test. The test is computed with the wntestq command in Stata 13.1.