Web-based supporting materials for "Building State Capacity through Public Land Disposal: An Application of RNN-Based Counterfactual Prediction" by Jason Poulos

Contents

1 Statistical significance

The following procedure constructs an exact distribution of *average* placebo effects under the null hypothesis:

1. Estimate the observed test static μ^* by estimating Eq. 8 (in the main text) for all J, which results in a matrix of dimension $(\tau - n) \times J$. Taking the row-wise mean results in a $\tau - n$-length array of observed average placebo treated effects.

2. Calculate every possible average placebo effect μ by randomly sampling (without replacement) which $J-1$ control units are assumed to be treated. There are $\mathcal{Q} = \sum_{g=1}^{J-1} \binom{J}{g}$ possible average placebo effects. The result is a matrix of dimension $(\tau - n) \times \mathcal{Q}$.[1]

3. Take a column-wise sum of the number of μ that are greater than or equal to μ^*.

Each element of the $(\tau - n) \times J$ matrix of counts obtained from the last step is divided by $\mathcal{Q}$ to estimate an array of exact two-sided p values, $\hat{p}$.

1.1 Randomization confidence intervals

I assume that treatment has a constant additive effect Δ and a construct an interval estimate for Δ by inverting the randomization test. Let δ_Δ be the test statistic calculated by subtracting all possible μ by Δ. I derive a two-sided randomization confidence interval by collecting all values of δ_Δ that yield $\hat{p}$ values greater than or equal to a significance level α. I find the endpoints of the confidence interval by randomly sampling 1,000 values of Δ.

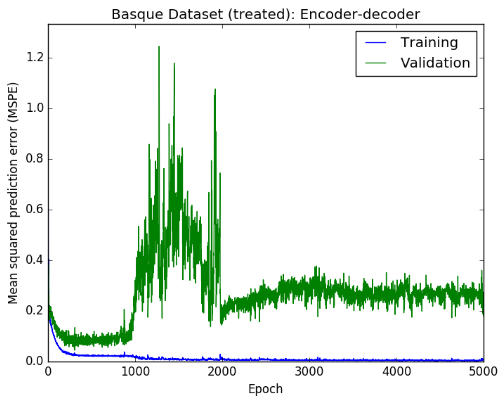
2 RNN architecture and implementation details

The baseline LSTM take the form of a single unidirectional RNN. The encoder takes the form of a two-layer bidirectional LSTMs, each with 128 hidden units, and the decoder is a single-layer Gated Recurrent Unit (GRU) (Chung et al. 2014) with 128 hidden units.

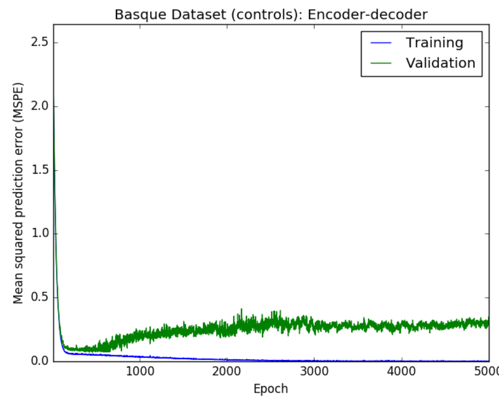
In the empirical applications, network weights are learned with stochastic gradient descent on $L^{(t)}$ using `Adam` stochastic optimization (Kingma and Ba 2014). As a regularization strategy, I apply dropout to the inputs and L2 regularization losses to the network weights.

3 RNNs training history: SCM datasets

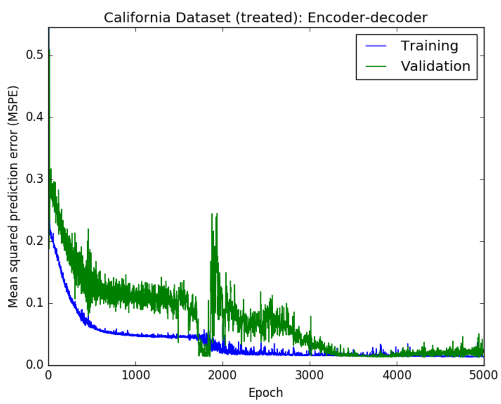
1. $\mathcal{Q}$ can be computationally burdensome when there are many control units. I set $\mathcal{Q} = 10,000$ in applications in which $J > 16$ (e.g., California dataset).



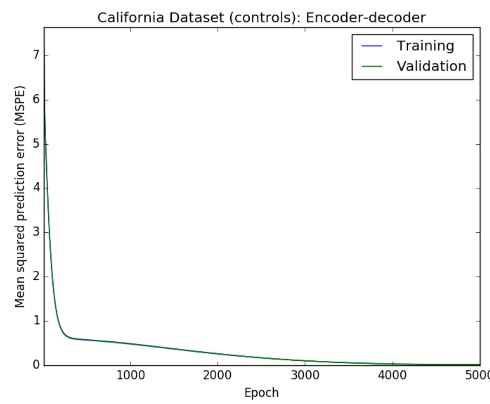
(a) Basque Country (treated)



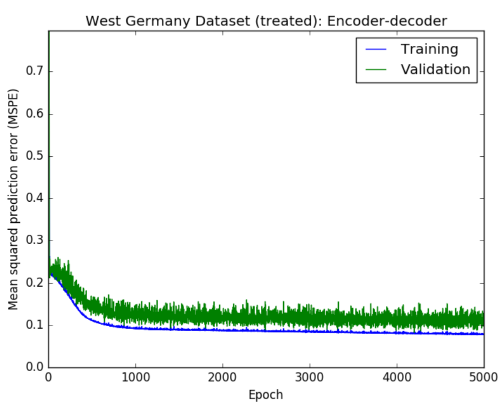
(b) Basque Country (controls)



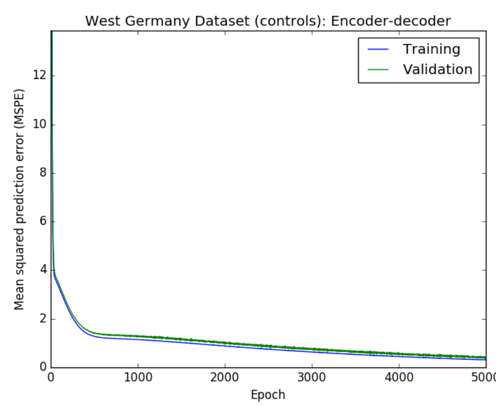
(c) California (treated)



(d) California (controls)

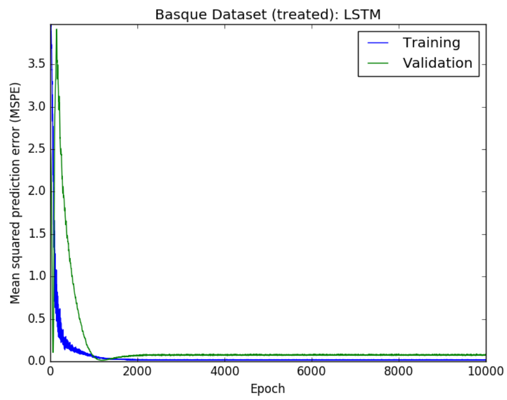


(e) West Germany (treated)

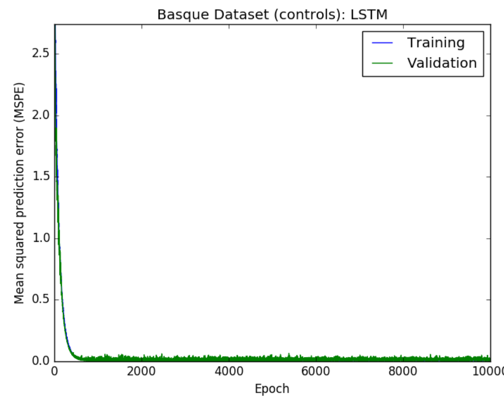


(f) West Germany (controls)

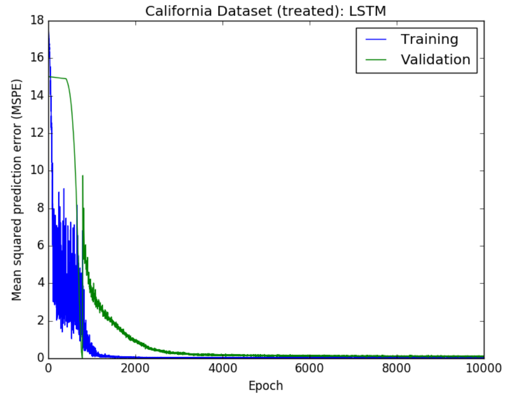
Figure 1: Evolution of encoder-decoder networks training and validation loss in terms of MSPE.



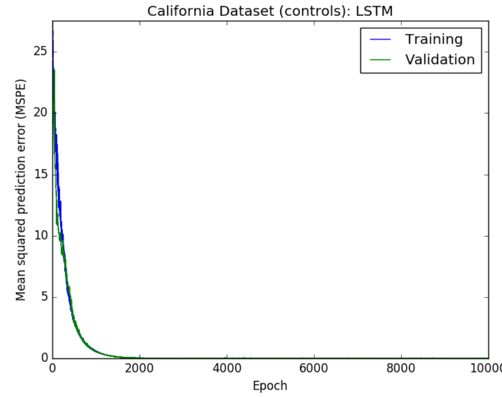
(a) Basque Country (treated)



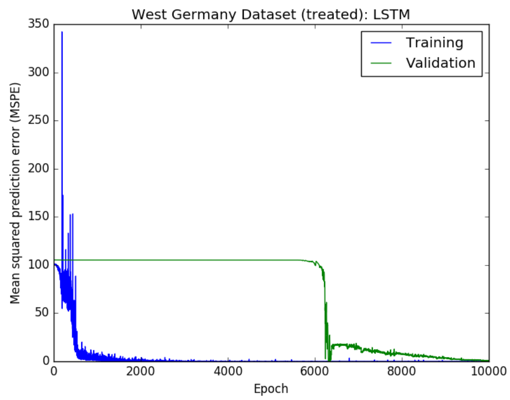
(b) Basque Country (controls)



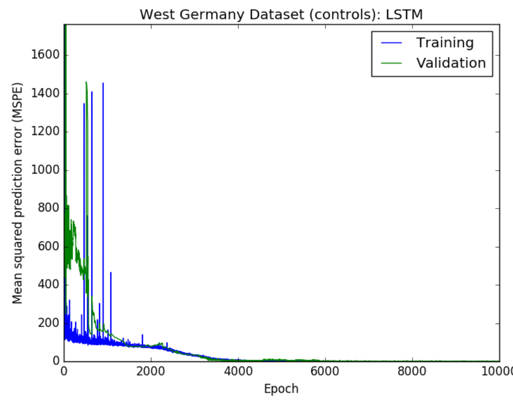
(c) California (treated)



(d) California (controls)



(e) West Germany (treated)



(f) West Germany (controls)

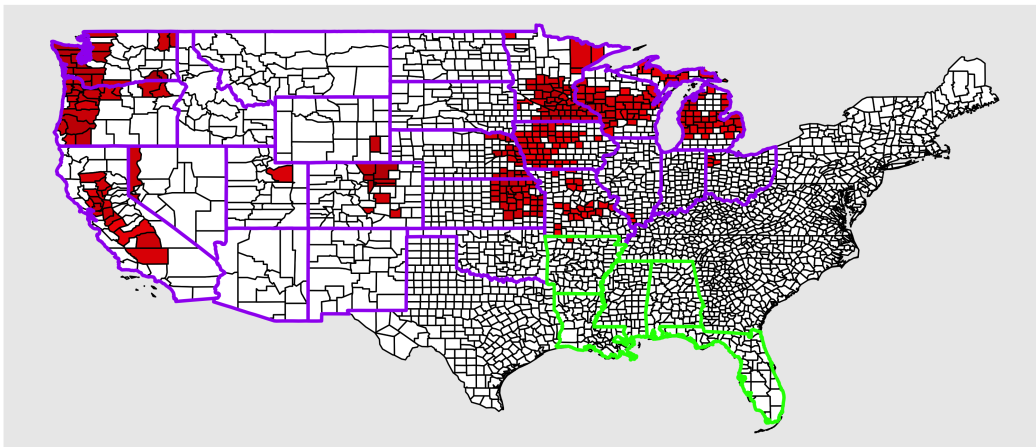
Figure 2: Evolution of LSTM training and validation loss in terms of MSPE.

4 Exploratory data analysis

Table 1: Definitions and sources of variables.

Theme	Variable	Coverage	Definition	Source
Farms	Farm value	1860-1950 (decennial)	Log average value of farmland and buildings per acre ($)	Haines (2010)
	Land inequality	Ibid.	Gini coefficient based on distribution of farm sizes, adjusted for the share of propertyless farmers (see Vollrath (2013, pg. 273))	Ibid.
State Capacity	Revenues	1790-1982	Log per-capita state government total revenue (1982$)	Sylla, Legler, and Wallis (1993, 1995a, 1995b) and Haines (2010) (total free pop. data from Haines (2010))
Ibid.	Expenditures	Ibid.	Log per-capita state government total expenditure (1982$)	Ibid.
Ibid.	Education spending	Ibid.	Log per-capita state government education spending (1982$)	Ibid.
Land patents	Homesteads	1860-1950	Log per-capita cumulative number patents issued under the Homestead Act of 1862	U.S. BLM (`https://glorecords.blm.gov`) (total free pop. data from Haines (2010))

Log per-capita cumulative homesteads in 1870



Log per-capita cumulative homesteads in 1900

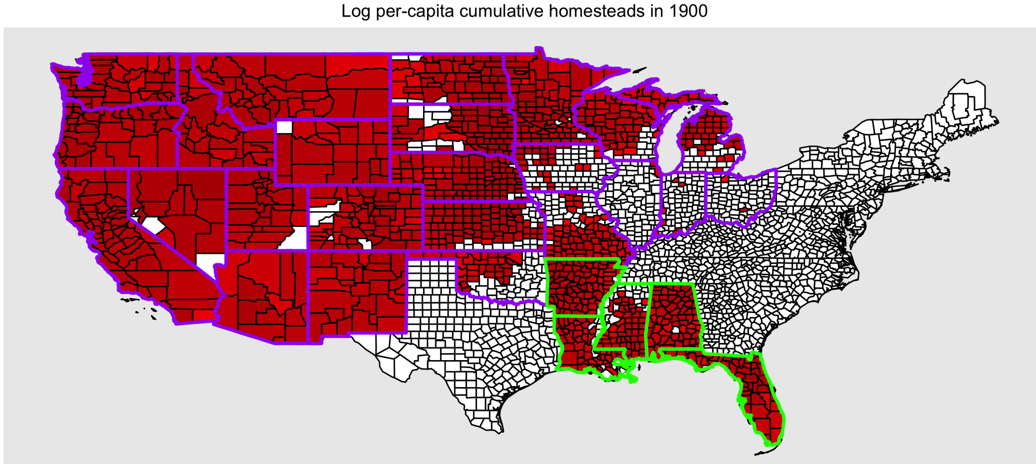


Figure 3: Log per-capita cumulative homesteads in 1870 and 1900, overlaid on 1911 county borders. Darker-colored counties have more higher values than lighter-colored counties, and white-colored counties have missing values. States bordered in green are southern public land states and those bordered in purple are western public land states. County border data from Long (1995).

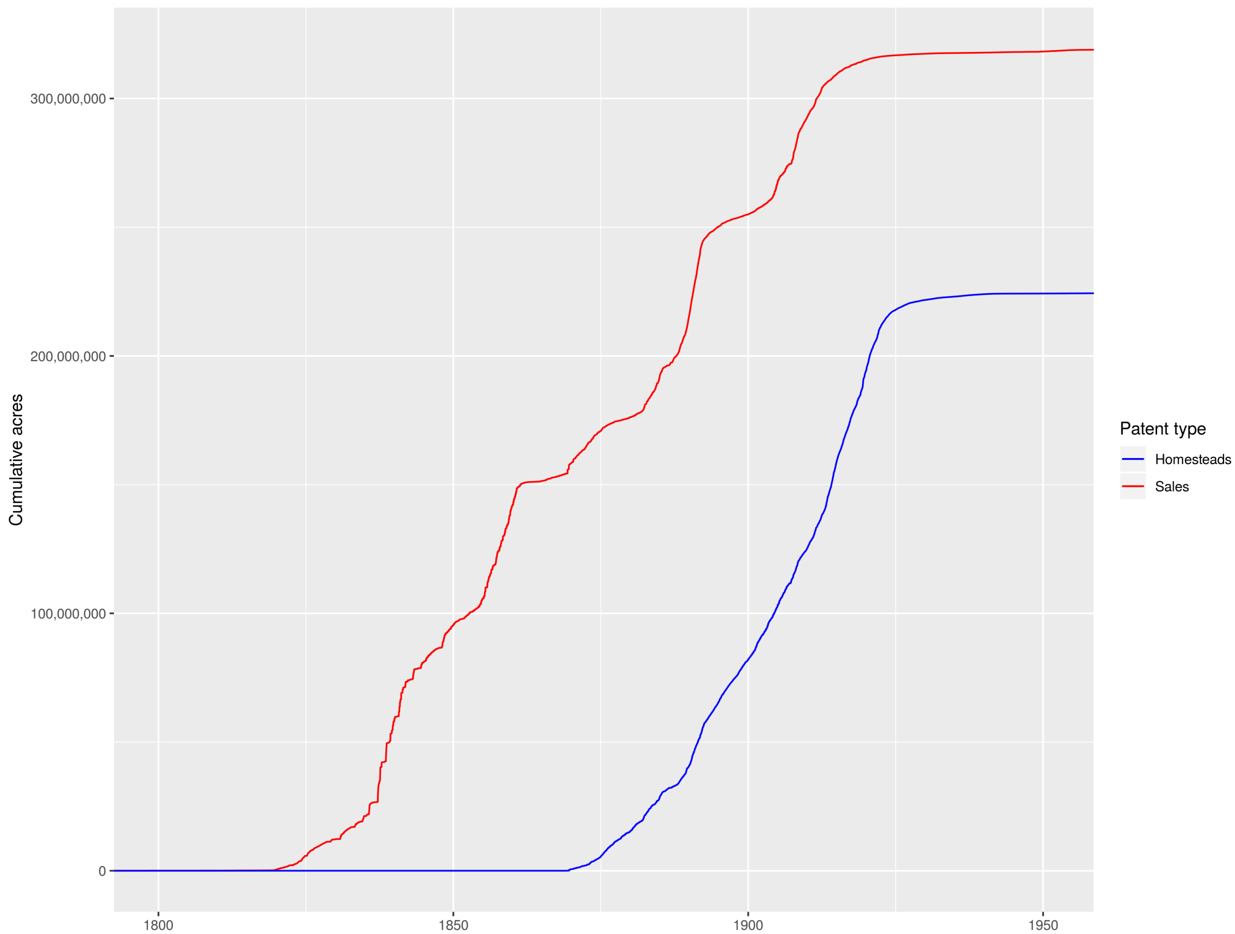
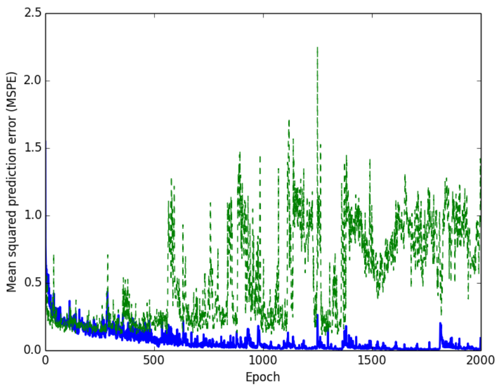
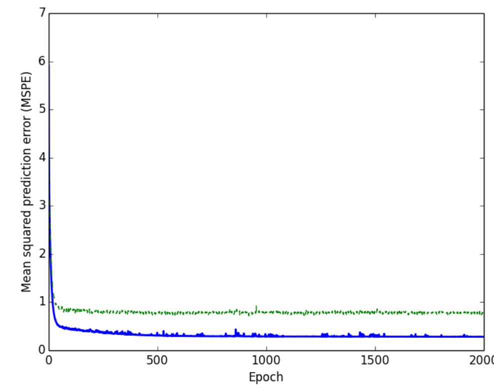


Figure 4: Cumulative total acres (by patent type) disbursed in public land states, 1800 - 1950.

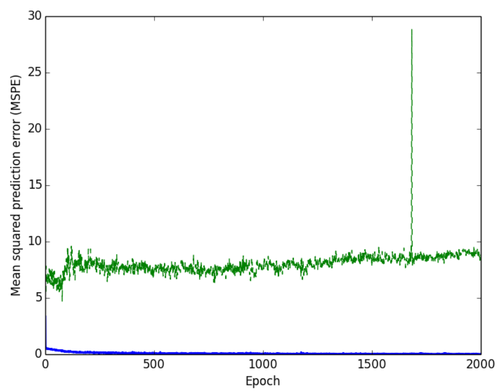
5 RNNs training history: State capacity data



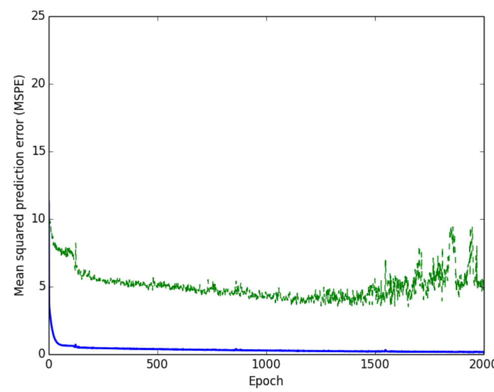
(a) Education Spending in South (treated)



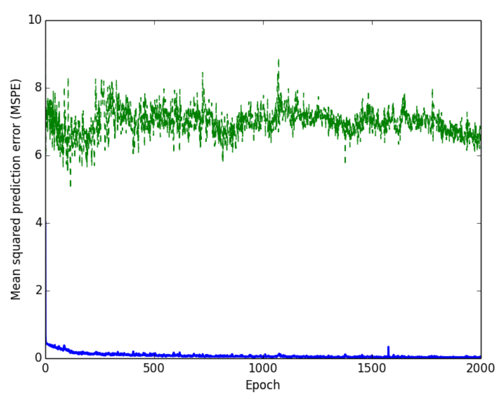
(b) Education Spending in South (controls)



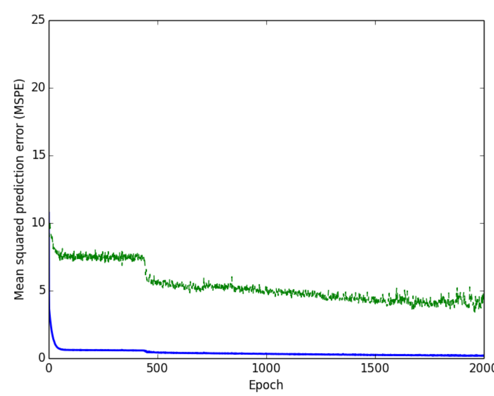
(c) Expenditure in South (treated)



(d) Expenditure in South (controls)

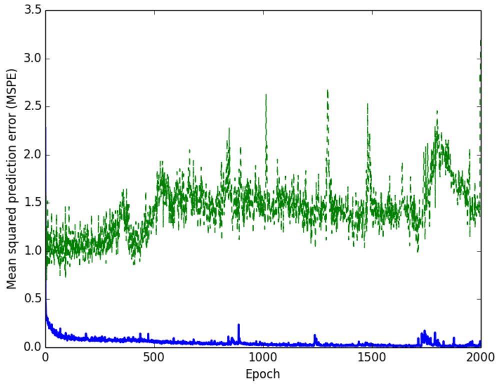


(e) Revenue in South (treated)

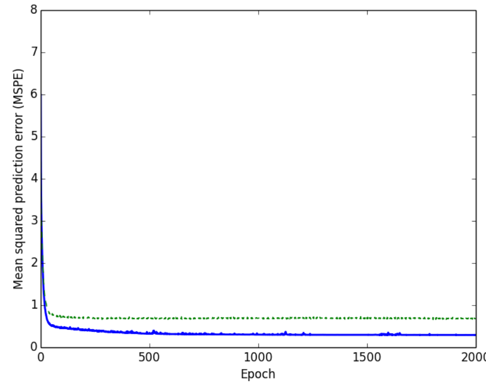


(f) Revenue in South (controls)

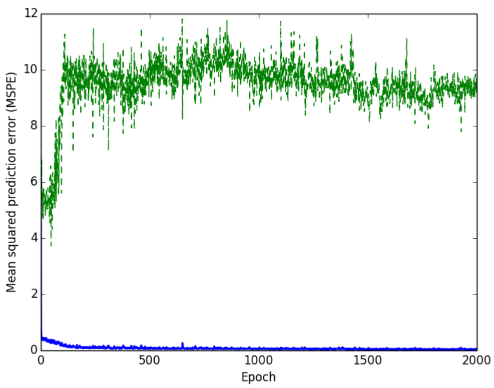
Figure 5: Encoder-decoder networks training (solid line) and validation loss (dashed line) on southern public land state capacity.



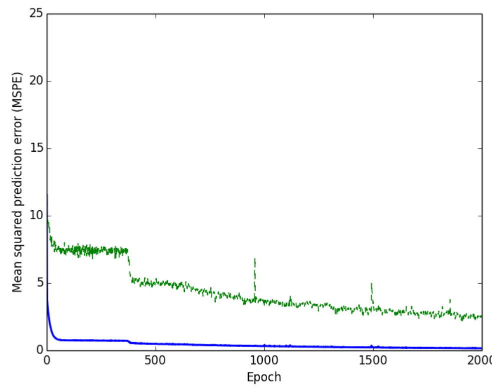
(a) Education Spending in West (treated)



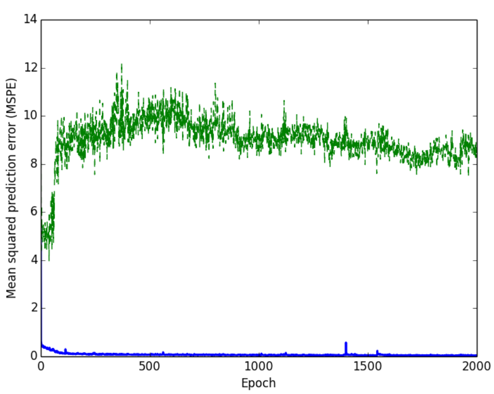
(b) Education Spending in West (controls)



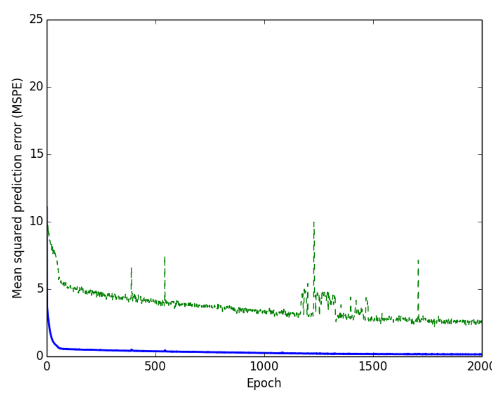
(c) Expenditure in West (treated)



(d) Expenditure in West (controls)



(e) Revenue in West (treated)



(f) Revenue in West (controls)

Figure 6: Encoder-decoder networks training (solid line) and validation loss (dashed line) on western public land state capacity.

6 RNNs and DD estimates

Table 2: Encoder-decoder FPR and MSPE on state capacity placebo tests.

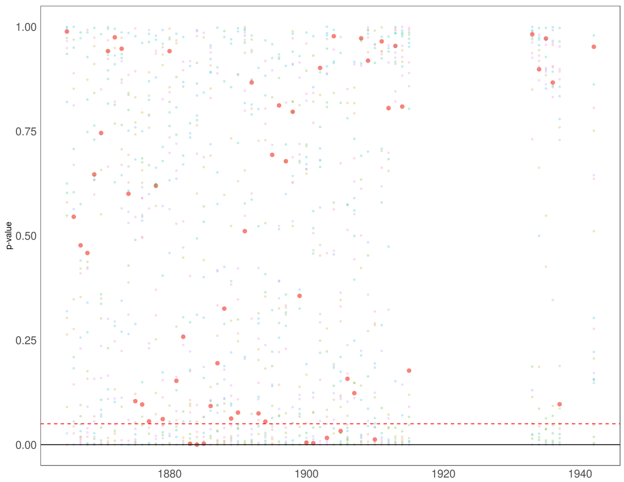
Outcome \ Measure	MSPE		FPR	
	South	West	South	West
Education spending	0.44 ± 0.59	0.37 ± 0.53	0.23	0.23
Expenditure	0.75 ± 0.2	0.47 ± 0.13	0.31	0.31
Revenue	0.8 ± 0.2	0.48 ± 0.2	0.28	0.28

Note: Errors represent ± one standard deviation from the MSPE.

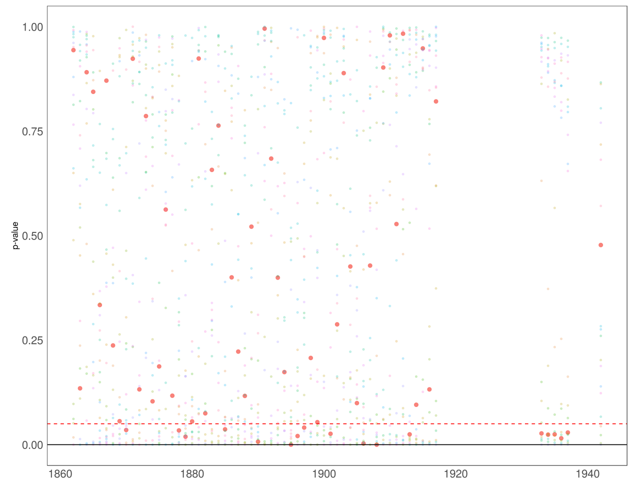
Table 3: LSTM FPR and MSPE on state capacity placebo tests.

Outcome \ Measure	MSPE		FPR	
	South	West	South	West
Education spending	0.55 ± 0.65	0.56 ± 0.83	0.22	0.19
Expenditure	6.66 ± 5.77	0.73 ± 0.23	0.36	0.27
Revenue	1.5 ± 3.37	1.68 ± 3.72	0.09	0.15

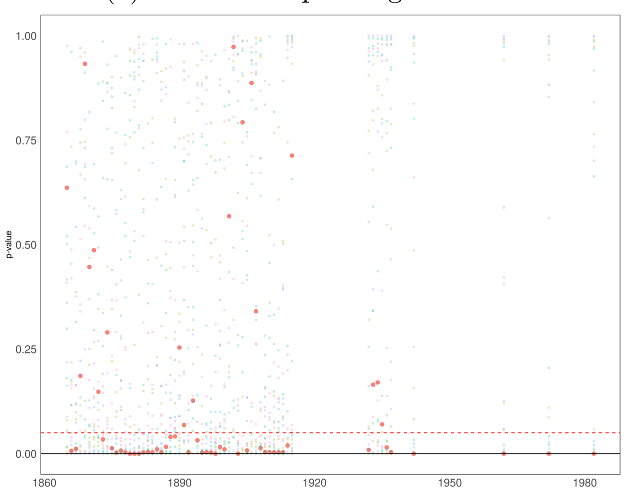
Note: Errors represent ± one standard deviation from the MSPE.



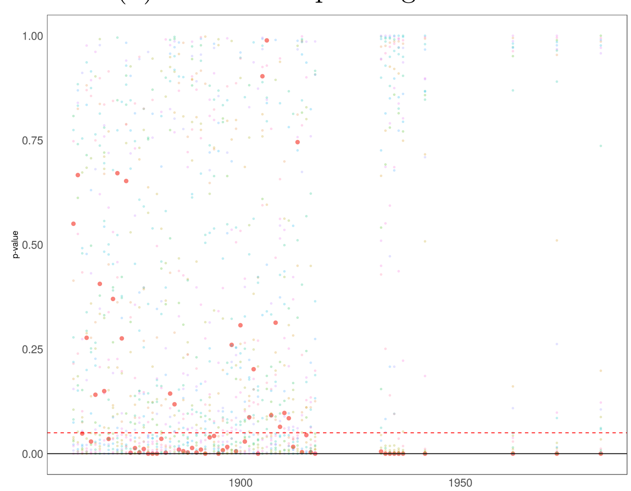
(a) Education spending in South



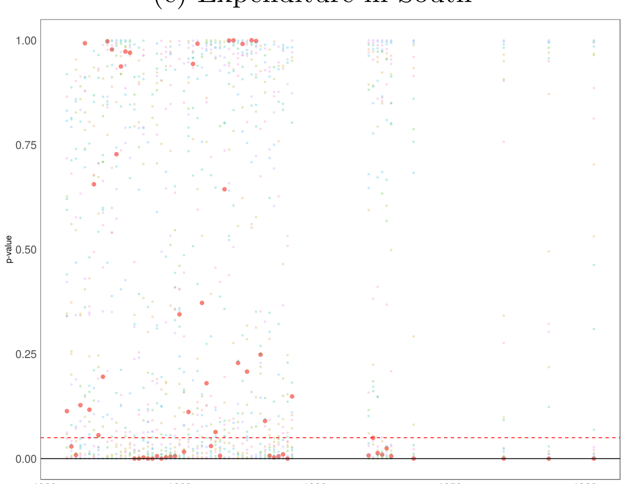
(b) Education spending in West



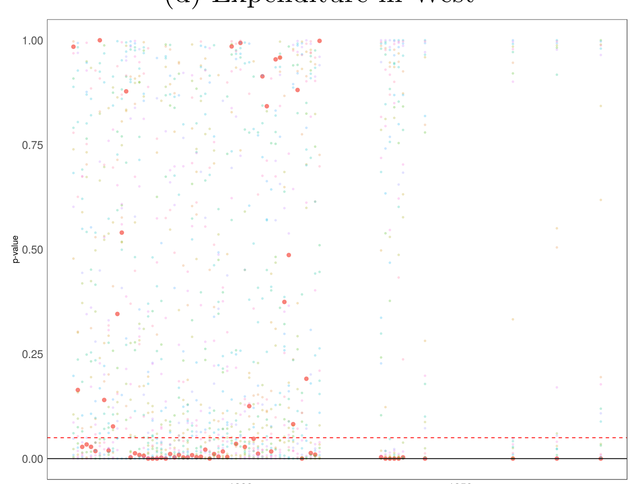
(c) Expenditure in South



(d) Expenditure in West



(e) Revenue in South



(f) Revenue in West

Figure 7: Encoder-decoder networks: Per-period randomization p-values corresponding to treatment effects on treated and control units in state capacity datasets. Darker dot represents p-values associated with treatment effects on the actual treated unit and lighter dots represent p-values associated with the effects on control units

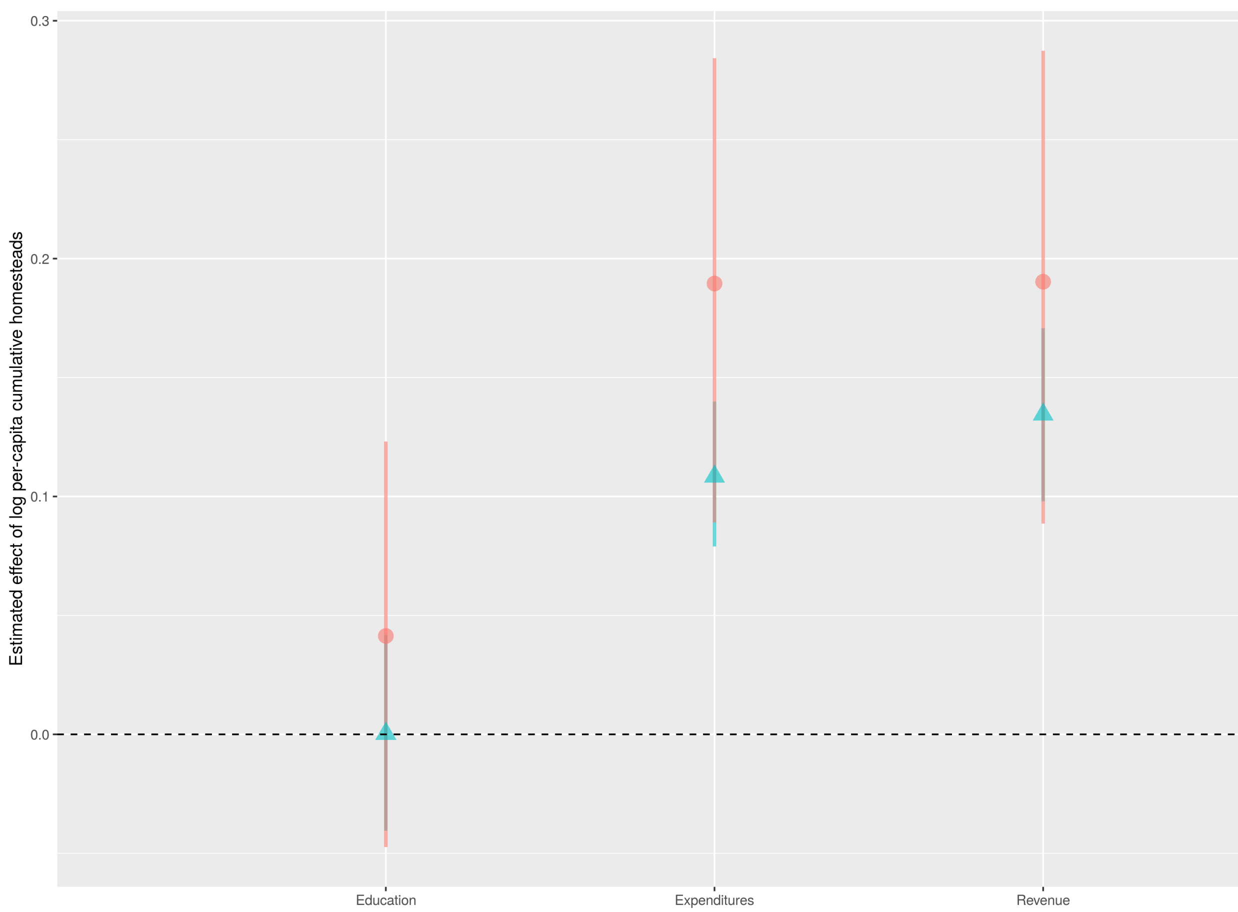


Figure 8: DD estimates of log per-capita cumulative homesteads on log per-capita state government finance, without including average farm values in the regression. See notes to Fig. 3.

7 Causal mechanisms

Table 4: DD estimates: Impact of log per-capita cumulative homesteads (county-level).

Outcome \ Region	South	West
Land inequality	-0.001 [-0.003, 0.0004], $N = 523$	-0.004 [-0.005, -0.002], $N = 2,002$
Land inequality (no farm values)	0.0007 [-0.0008, 0.002] , $N = 590$	-0.001 [-0.002, -0.0001], $N = 2,549$
Railroad access	0.03 [0.01, 0.05], $N = 350$	0.09 [0.07, 0.1], $N = 1,053$
Railroad access (no farm values)	0.06 [0.04, 0.08], $N = 361$	0.12 [0.11, 0.13], $N = 1,251$

Note: Values in brackets represent 95% confidence intervals constructed using 1,000 state-stratified bootstrap samples.

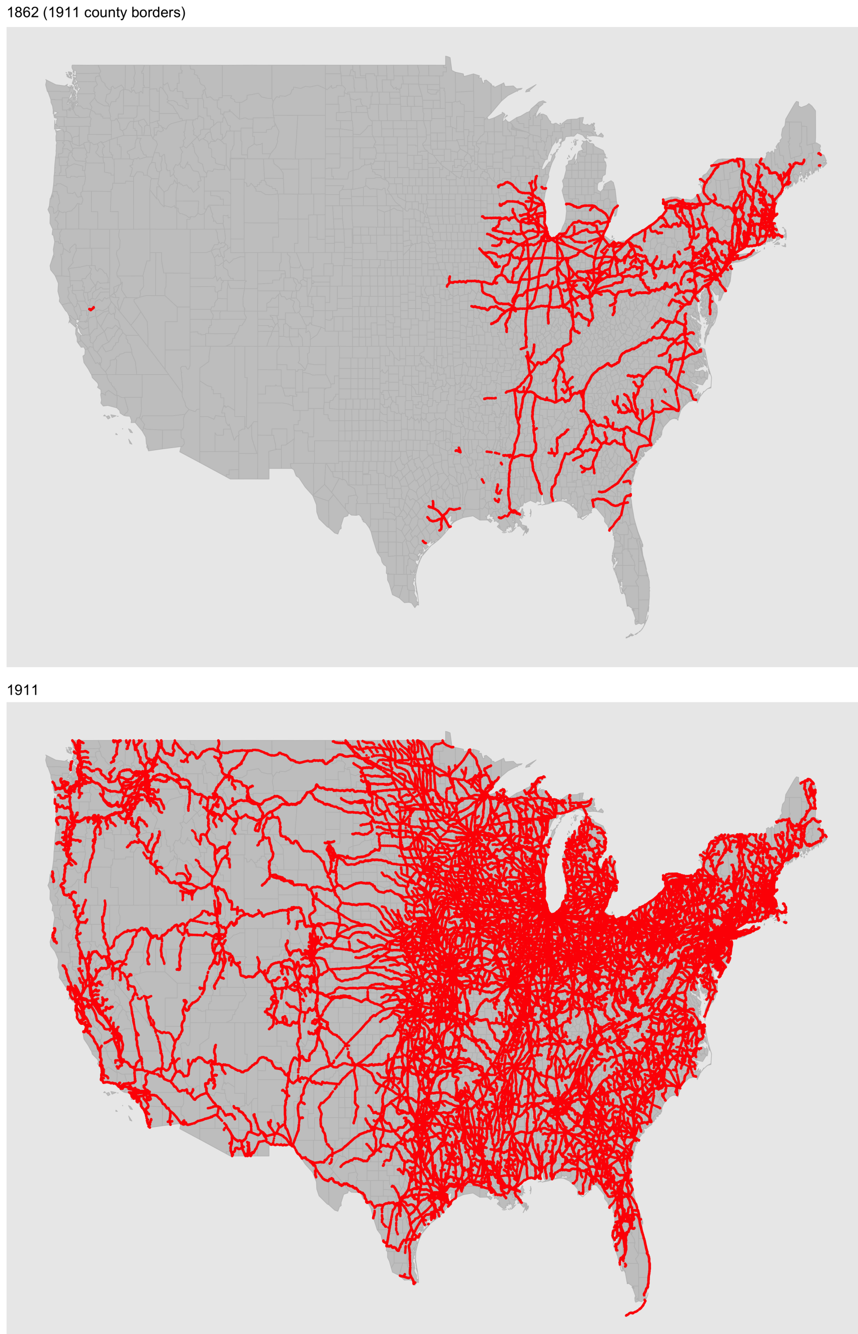


Figure 9: Railroad lines in 1862 and 1911, overlaid on 1911 county borders. Railroad data from Atack 2013 and county border data from Long 1995.

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