Cultural Change

Evidence from Three Centuries of U.S. Local Newspapers

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Analyzing cultural change via historical texts

- Historical text documents are increasingly used to study cultural change when conventional survey data are not available
 - For example, historical books, newspapers, parliamentary or presidential speech
- Assumption: the text reflects the culture of the people who read, wrote or spoke it
- These studies typically rely on **time series data** and **cannot leverage spatial variation**, making it hard to examine causality

This project: a database of local culture from digitized US newspapers

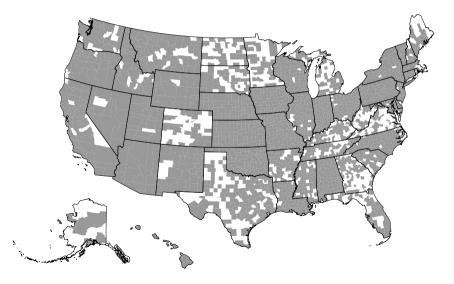
- We access **more than 1B pages** of local newspapers available through **newspapers.com**, **newspaperarchive.com** or **chroniclingamerica.gov**
- We can link newspaper text to key metadata: newspaper name, publication date, page, city of publication, circulation, political affiliation, and more
- The database covers 2,405 U.S. counties from all states and goes back to the 1700s
- Newspaper markets in the U.S. have been **highly local** only one (two) daily newspaper in 77% (14%) of counties between 1869 and 2004 Gentzkow + 2011

Limitations of our newspaper data

- Full-text access for around 25% of the corpus, otherwise access to frequencies of keywords and keyword combinations at the page level
- Poor OCR quality, especially for older newspapers, and no article segmentation
- We will assess the importance of these issues for our goals by replicating our measurement using the corpus recently published by Dell et al.
- Their corpus has better OCR quality and segmented articles for approx. 20M pages

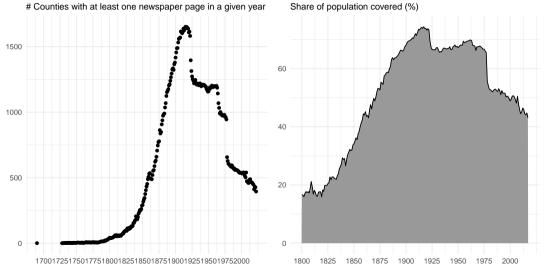
Newspaper database covers 2,405 counties from all states

newspapers.com
 newspaperarchive.com



Number of counties covered unbalanced over time

newspapers.com



Today, focus on a specific cultural trait: norm tightness

Sources: Harrington, Gelfand (PNAS, 2014); Jackson et al. (Nature Human Behavior, 2019)

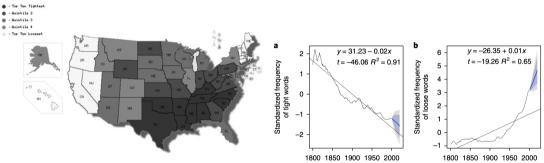


Fig. 1. Patterns of tightness-looseness at the state level in the United States. States are organized into quintiles based upon tightness-looseness index scores. This map was constructed at www.diymaps.net.

Fig. 1 | Frequencies in tight and loose words in books from 1800 to 2000.

Year

Year

How we measure norm tightness from newspaper text

- The literature knows **two types of approaches** to detect concepts, such as norm tightness, from text:
 - 1. **Dictionary-based:** Create a dictionary of words that are semantically close to the concept of interest and count their frequency in the text
 - 2. Algorithmic-based: Use a machine learning algorithm to detect the concept of interest from the text
- Both approaches have advantages and disadvantages:
 - **Dictionary-based:** transparent, but coarse
 - Algorithmic-based: often higher accuracy, but opaque (and limited to full-text corpora)
- We use two approaches and compare their performances:
 - 1. Dictionary augmented with machine judgement
 - 2. Contextualized Construct Representation (CCR), which is based on BERT (a language model that captures contextual semantic information)

Method: dictionary-based approach

- We draw on the Tight-Loose dictionary created by Jackson et al. (NHB, 2019)
- The dictionary contains 2x20 keywords whose Google News *word2vec embeddings* are close to the *embeddings* of 2x8 seed words related to Tight-Loose theory
- *Embeddings* are vectors of numbers that represent the meaning of a word based on co-occurrence across the whole corpus; intuitively, words that appear in similar corpus contexts get similar vectors

Norm Tightness =
$$\operatorname{Avg}_t \left[\operatorname{Scale} \left[\frac{\# \operatorname{tight} \operatorname{word}_t}{\operatorname{doc} \operatorname{length}} \right] \right] - \operatorname{Avg}_t \left[\operatorname{Scale} \left[\frac{\# \operatorname{loose} \operatorname{word}_t}{\operatorname{doc} \operatorname{length}} \right] \right]$$

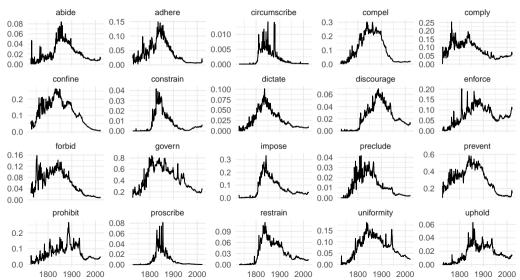
where a document is all newspaper text in newspaper i located in county c in year t

Tight words: restrain, prevent, comply, constrain, uniformity, adhere, enforce, proscribe, abide, dictate, circumscribe, impose, uphold, discourage, compel, forbid, confine, govern, prohibit, preclude. Loose words: allow, freedom, create, variability, autonomy, openness, leeway, flexibility, broadmindedness, transformatory, customize, subjectivities, modify, limitless, empower, adaptiveness, pluralism, personalize, encourage, diverse

Method: refining and validating the dictionary

- Semantic substitution: Substitute each word with semantically closest neighbor, then recompute the construct of interest and report its correlation with the original measure ($\rho \approx 1$)
- **Part-of-speech balancing:** We augment the dictionary by balancing nouns, verbs, adjectives, adverbs, etc.
 - e.g., if dictionary contains prohibit, we add prohibited, prohibiting, prohibition, prohibitive, and prohibitively
 - ho=0.896
- Validation against proxy measure from the literature (in four slides)

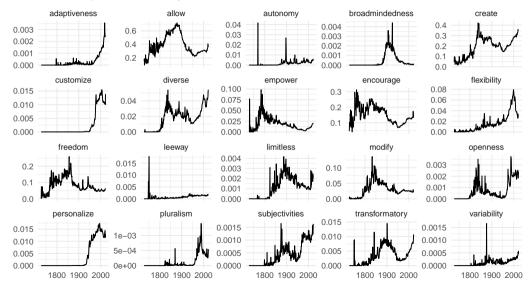
Relative frequency of tight words in newspapers <a>here rewspaperarchive.com



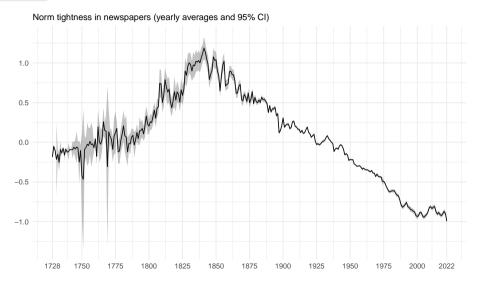
Relative frequencies of tight keywords

Relative frequency of loose words in newspapers . newspaperarchive.com

Relative frequencies of loose keywords

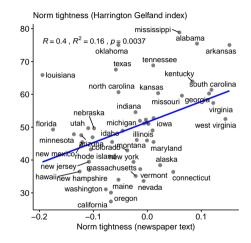


Frequency of tight vs. loose words in newspapers from 1728 to 2022



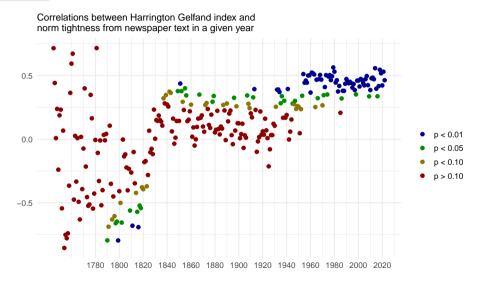
Does the text-based measure correlate with conventional psych data?

newspaperarchive.com



Data shown on y-axis are from Harrington Gelfand (PNAS, 2014).

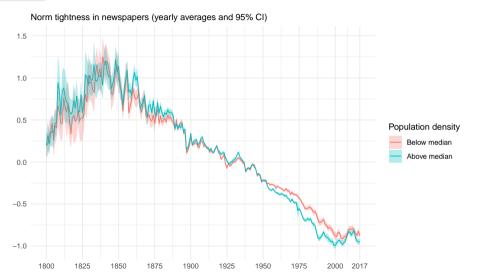
Text after 1950 highly correlated with modern psych data



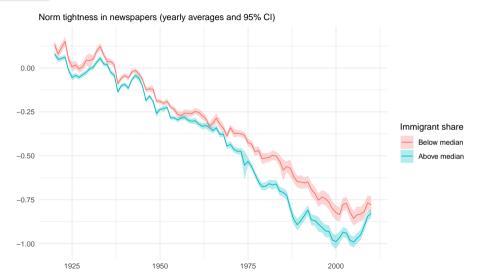
Decade-by-decade rank correlations suggest break during 1940s



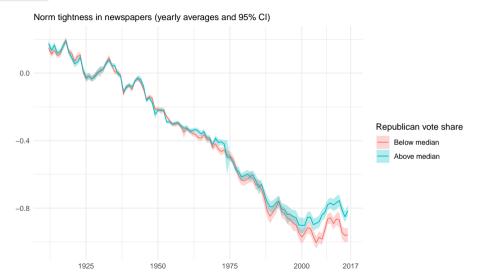
Urban newspapers increasingly looser than rural ones after 1950



Newspapers in high-immigration places increasingly looser after 1970

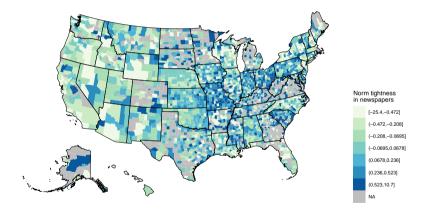


Newspapers in Republican places increasingly tighter after 2000



Norm tightness across US counties

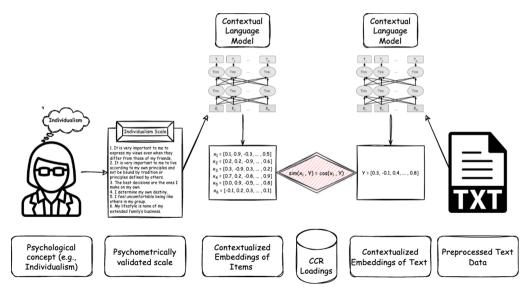
averaged over all years • averaged over 1950-2022



^{ho=} 0.81 between norm tightness averaged over all years and averaged over 1950 to 2022

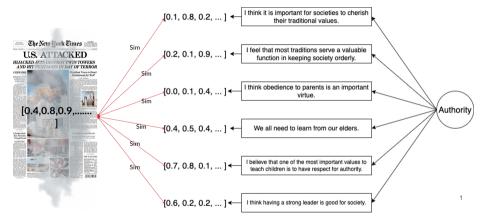
Method: contextualized construct representation (CCR)

Source: Atari, Omrani, Dehghani (2023)



Method: contextualized construct representation (CCR)

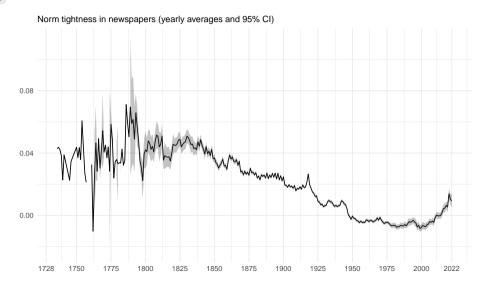
Source: Atari, Omrani, Dehghani (2023)



Survey questions: 1. There are many social norms that people are supposed to abide by in this country. 2. In this country, there are very clear expectations for how people should act in most situations. 3. People agree upon what behaviors are appropriate versus inappropriate in most situations this country. 4. People in this country have a great deal of freedom in deciding how they want to behave in most situations. 5. In this country, if someone acts in an inappropriate way, others will strongly disapprove. 6. People in this country almost always comply with social norms.

CCR-based measure of norm tightness

Validation



- Hope you're convinced that we're capturing some aspects of norm tightness in newspapers
- Let's put this to work by testing core hypotheses of cultural evolution theory:
 - Do adverse shocks tighten social norms?
 - Do looser norms promote innovation?

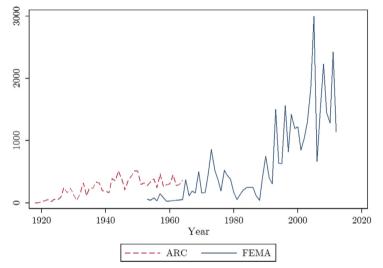
Do natural disasters tighten social norms?

- Data: all U.S. federally designated natural disasters from 1918 to 2012, aggregated to county-decade level Boustan + 2020
- Empirical strategy: standard difference-in-differences equation

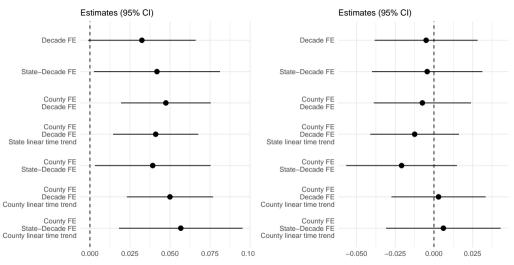
Tightness_{c(s)t} = β Severe disaster indicator_{c(s)t} + α_c + α_t + $\gamma \times (X_{c(s)} \times t) + \varepsilon_{c(s)t}$

- *c, s, t* denote county, state, year
- Severe disaster indicator = 1 if a disaster with \geq 25 fatalities occurs b/w t 10 and t
- α_c and α_t : county and decade fixed effects
- $X_{c(s)} \times t$: state or county-specific linear time trends, removing local factors that smoothly change over time (e.g., local long-term economic progress)
- Standard errors clustered on counties

Annual disaster count in U.S. from 1918 to 2012 trends upwards



Natural disasters increase norm tightness in newspapers



 \Rightarrow Severe disasters increase norm tightness by \approx 0.05 s.d. or 5% of gap b/w VT and AR

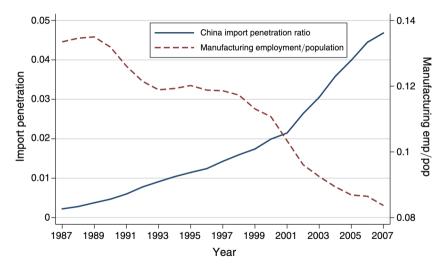
Do adverse economic shocks tighten social norms?

- Data: Exogenous variation in local U.S. labor market condtions induced by trade with China b/w 1990 and 2007 the "China Shock" Autor + 2013
- Empirical strategy: First-difference equation

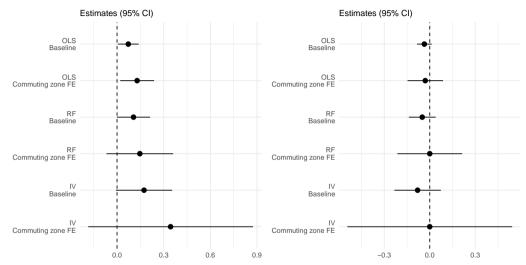
 Δ Tightness_{*c*(*r*)*t*} = $\beta \Delta$ Local trade exposure_{*ct*} + $X_c \gamma + \alpha_r + \alpha_t + \varepsilon_{c(r)t}$

- c, r, t denote commuting zone, census-region, period
- Δ Local trade exposure is change in local import competition with China from t 1 to t
- X_c: baseline employment share in manufacturing
- α_r : census-region fixed effects, removing regional factors that smoothly change over time
- α_t : period-fixed effects, absorbing time-variant factors affecting all commuting zone
- Standard errors clustered on states

Local trade exposure and manufacturing employment in U.S.



Adverse economic shocks increase norm tightness in newspapers



 \Rightarrow Positive estimates of effect of trade exposure (left), while no pre-trend (right)

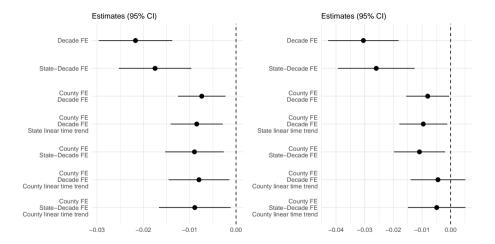
Does norm tightness affect innovation?

- Data: Comprehensive Universe of U.S. Patents (CUSP); all patents issued by the USPTO between 1836 and 2015, aggregated to county-decade level Berkes 2018
- Empirical strategy: standard difference-in-differences equation

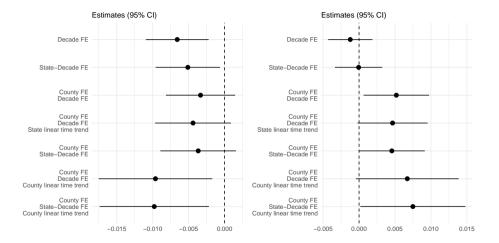
Patents p. 10,000 $\text{ppl}_{c(s)t} = \beta \text{ Tightness}_{c(s)t} + \alpha_c + \alpha_t + \gamma \times (X_{c(s)} \times t) + \varepsilon_{c(s)t}$

- *c, s, t* denote county, state, decade
- **Patents p. 10,000 ppl**: number of patents filed b/w *t* and *t* + 10 normalized by county population in *t*
- **Tightness**: avg. tightness among newspapers in *i* b/w *t* and t + 10
- α_c and α_{st} : county and decade fixed effects
- $X_{c(s)} \times t$: state or county-specific linear time trends, removing local factors that smoothly change over time (e.g., local long-term economic progress)
- Standard errors clustered on counties

Norm tightness associated with fewer patents p.c., but pretrend



Adding one-period lagged dependent variable

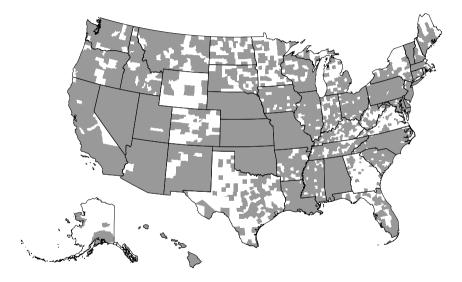


Take-aways

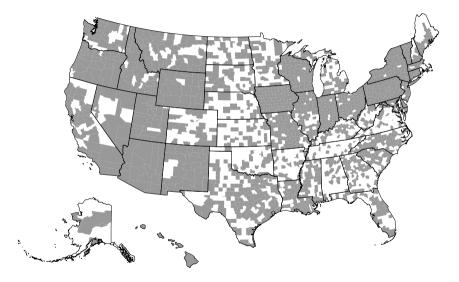
- We study historical psychology through the lens of thousands of local newspapers from all U.S. states and going back to the 1700s
- Consistent with previous studies, we find norms in the U.S. loosened over the past 200 years, while local adverse shocks causes local tightening
- Looser norms are associated with more innovation
- Next steps: measuring more traits (e.g., individualism, moral universalism, religiosity, honor culture, gender norms, etc.)

Appendix

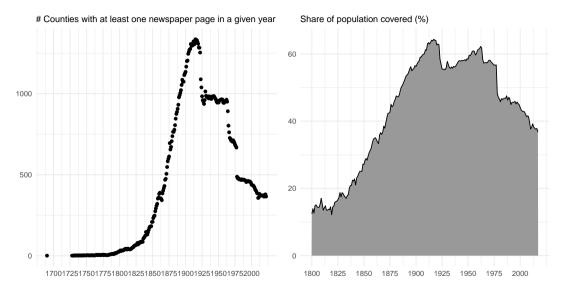
Newspapers.com database covers 2,057 counties from all states • Back



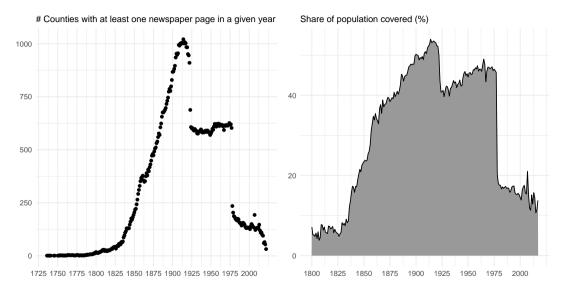
Newspaperarchive database covers 1,866 counties from all states **PBOR**



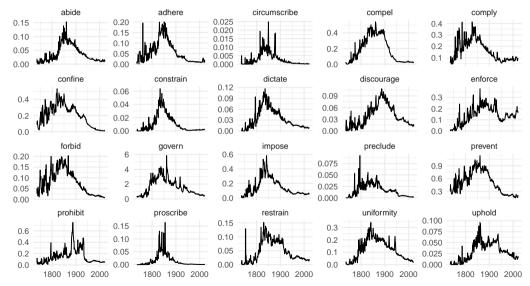
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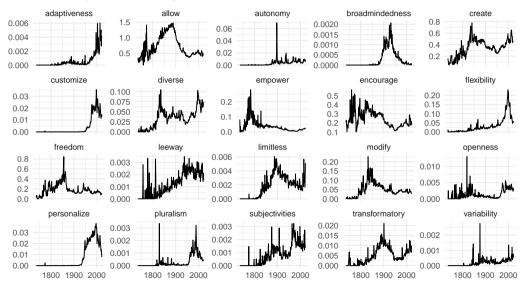
Newspaperarchive database • Back

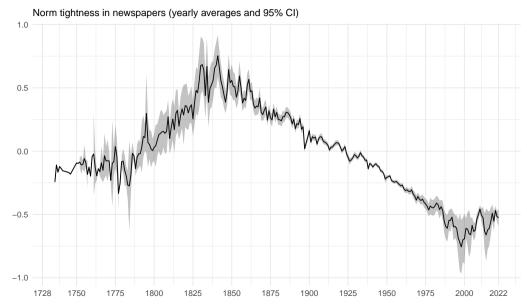


Relative frequencies of tight keywords



Relative frequencies of loose keywords

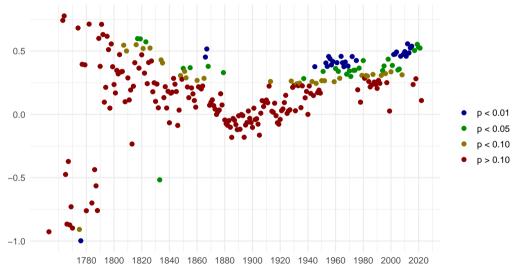


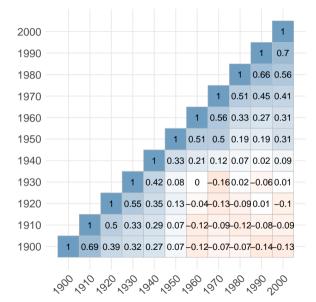


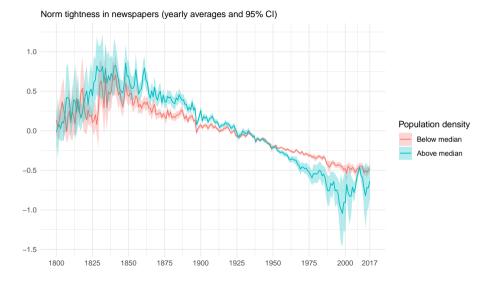
Norm tightness (Harrington Gelfand index) 80. mississippi R = 0.29, $3^{+2} = 0.085$, p = 0.04arkansas oklahoma 70tennessee louisiana e texas kentuckv north carolina south carolina 60 • missouri georgia kansas virginia Idiana delaware • 50 florida rhode sla new york coloradew jerse alaska 40 vermon hawaii nevada maine -washington 30 california[®] oregon -0.25 0.00 0.25 0.50 Norm tightness (newspaper text)

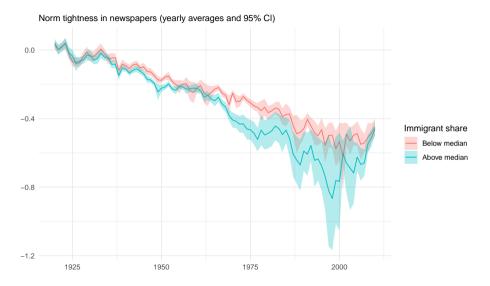
Data shown on y-axis are from Harrington Gelfand (PNAS, 2014).

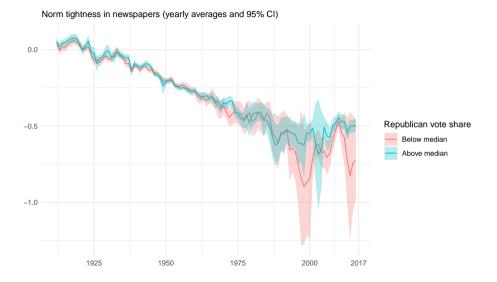
Correlations between Harrington Gelfand index and norm tightness from newspaper text in a given year











Norm tightness across US counties

averaged over 1950-2022
Back

