

Order and Chaos in Business Cycle Narratives

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Motivation

- ▶ **Shiller (2017) calls for rigorous treatment of narratives.**

“We have to consider the possibility that sometimes the dominant reason why a recession is severe is related to the prevalence and vividness of certain stories ...The field of economics should be expanded to include serious quantitative study of changing popular narratives.”

Introduction

- ▶ **Contribute to establishment of “narrative economics” literature.**
 - ▶ Shiller (2017), Nimark and Pitschner (2019), and Chahrour et al. (2019).
- ▶ **Measure and describe orderliness of business cycle narratives.**
 - ▶ Dominant narrative needed to coordinate behavior across households.
- ▶ **Leave causality discussion to future work.**
 - ▶ Difficult to establish in any time series context.

Introduction

Preview of Findings

1. Narratives become ordered during expansions and fragmented during contractions.
2. Important or prevalent narratives tend to be more orderly.
3. The presence of a historical precedent increases the orderliness of narratives.

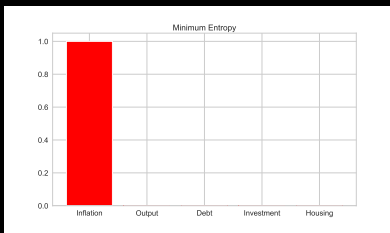
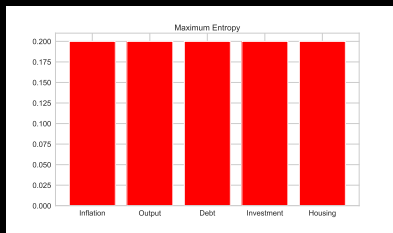
Data

- ▶ **Collect data from Swedish newspaper archive over 1950-2019.**
 - ▶ Description of business cycles uniform over period.
- ▶ **Concentrate on business cycle narratives in large national newspaper.**
 - ▶ Stable newspaper composition and use of terminology.
 - ▶ Total of 62,506 passages.
- ▶ **Clean text and encode in numerical format.**
 - ▶ Use low-dimensional, dense representation (embeddings).
 - ▶ Fine-tune pre-trained embeddings for Swedish language (Fallgren et al. 2016).

Methods

- ▶ Measure disorder using entropy.

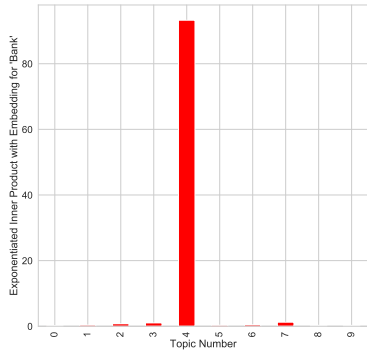
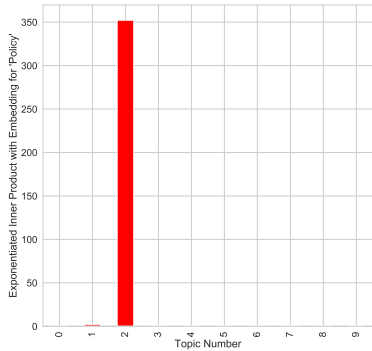
$$H(p) = - \sum_{n \in N} p_n \log_2(p_n) \quad (1)$$



Methods

- ▶ **Model narratives using state-of-the-art NLP (Blei et al. 2019).**
 - ▶ Dynamic topic model.
 - ▶ Topic and vocabulary embeddings.
- ▶ **Model capable of handling large vocabulary.**
 - ▶ Important for long time series.
- ▶ **Generates more interpretable topics.**
 - ▶ Query embeddings.
 - ▶ Compare embeddings at different points in time.

Methods



Methods

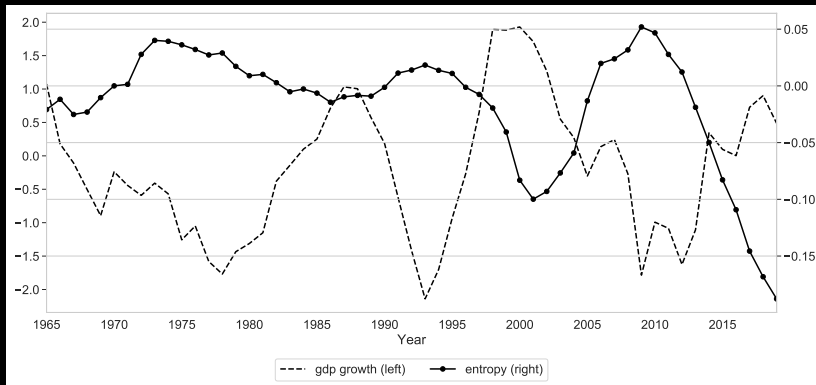
Model Output

| Parameter | Description | Dimension |
|-----------|-----------------------|-----------------------|
| α | topic embeddings | $T \times L \times K$ |
| ρ | vocabulary embeddings | $L \times N$ |
| ν | vocabulary | $N \times 1$ |
| θ | topic proportions | $T \times K$ |

$$T = 69, L = 300, K = 10, N = 1965$$

Results

GDP Growth and Entropy



Results

Topic Importance and Entropy

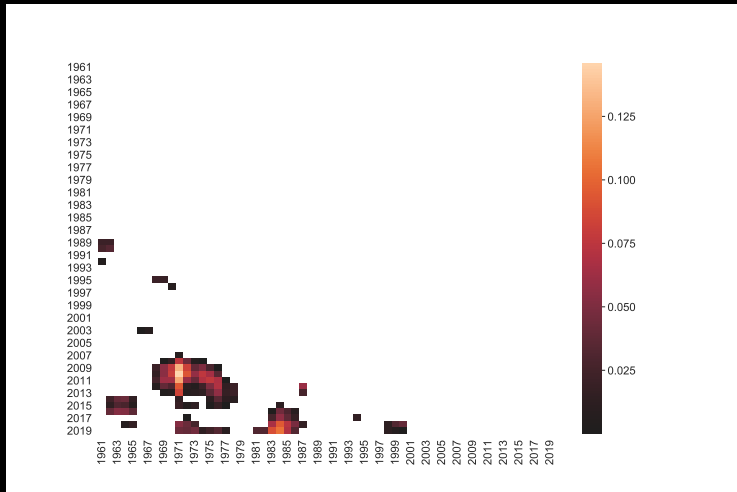
- ▶ **Model yields time series of topic proportions, θ_k^t .**
 - ▶ Provide measure of extent of coverage at point in time.
- ▶ **Growth-related topics spike in importance at business cycle turning-points.**
 - ▶ Examine relationship between importance and entropy.

Memory and Entropy

- ▶ **Blei et al. (2019) model topics as embeddings.**
 - ▶ Inner product of embeddings at two points in time yields measure of similarity: $\alpha_k^{t'} \alpha_k^{t-s}$.
- ▶ **Detrend embeddings to eliminate long-run drift.**
 - ▶ Use inner product to identify similar past events.
- ▶ **Construct “memory,” which indicates that a past event was described similarly by media.**
 - ▶ Include share of events with memory in regression.

Results

Heatmap of Memory for "Bank" Topic



Results

Regression Specification

$$H(\alpha_k^t) = c + \beta y^t + \gamma \theta_k^t + \zeta_k^t + \epsilon_k^t \quad (2)$$

- ▶ $H(\alpha_k^t)$ = detrended within-topic entropy.
- ▶ y^t = detrended GDP growth.
- ▶ θ_k^t = topic proportion.
- ▶ ζ_k^t = share of past events with memory.

Results

Table: Entropy Regression Results

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|----------------------------------|---------------------|-----------------------|----------------------|---------------------|-----------------------|-----------------------|-----------------------|
| <i>gdp_growth</i> | -0.055** (0.023) | | | | -0.055** (0.022) | | -0.052** (0.023) |
| <i>accelerations</i> | | | -0.069*** (0.021) | | | | |
| <i>decelerations</i> | | | | 0.093*** (0.030) | | | |
| <i>no_accelerations</i> | | 0.3055*** (0.0784) | | | | | |
| Δ <i>topic_proportion</i> | | | | | -0.6627** (0.2770) | | |
| <i>memory_share</i> | | | | | | -35.894*** (5.707) | -35.576*** (5.685) |
| R^2 | 0.0076 | 0.0217 | 0.0154 | 0.0129 | 0.0149 | 0.0717 | 0.0794 |
| <i>N</i> | 640 | 640 | 640 | 640 | 640 | 500 | 500 |

Conclusions

1. Narratives consolidate during expansions and fragment during contractions.
2. Topics tend to be more ordered when they receive more coverage.
3. Existence of similar past events leads to convergence to dominant narrative.