

Influence in the United States Senate

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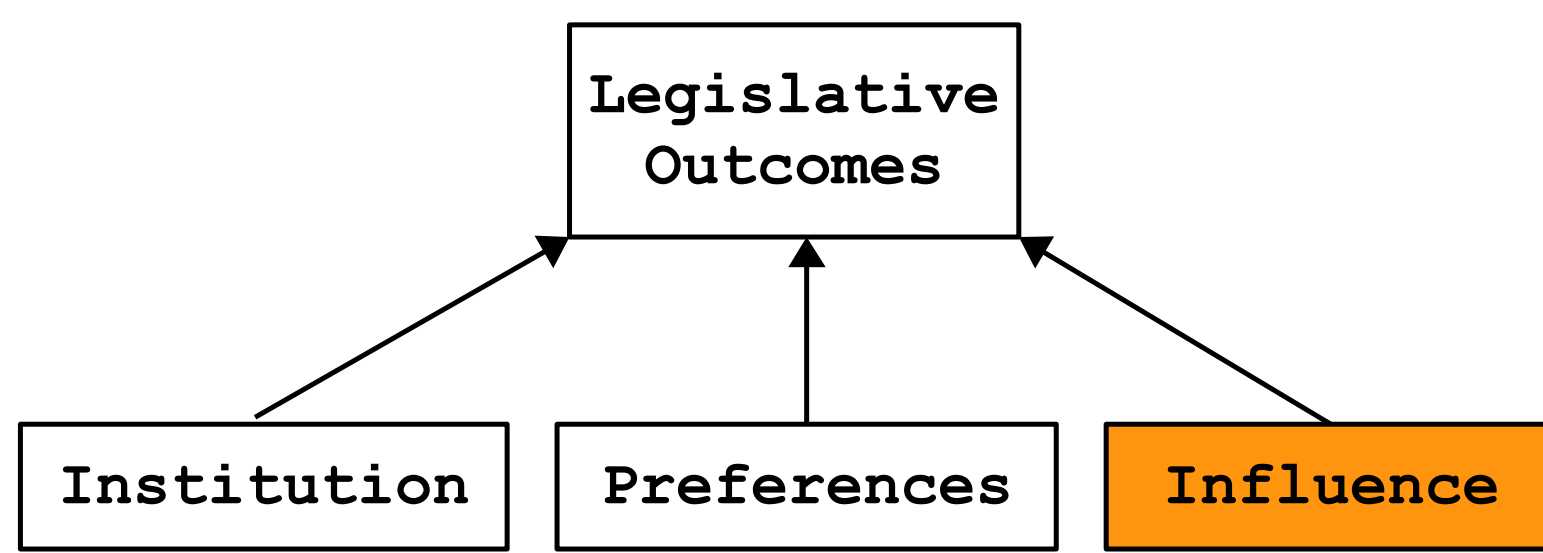
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Research Objectives

- Cast legislative influence in a relational framework.
- Introduce a new measure of legislative influence.
- Infer latent influence networks.
- Asses the power of the new measure in predicting legislative outcomes in the Senate.

Influence

Influence relations are a missing component in explaining legislative outcomes:

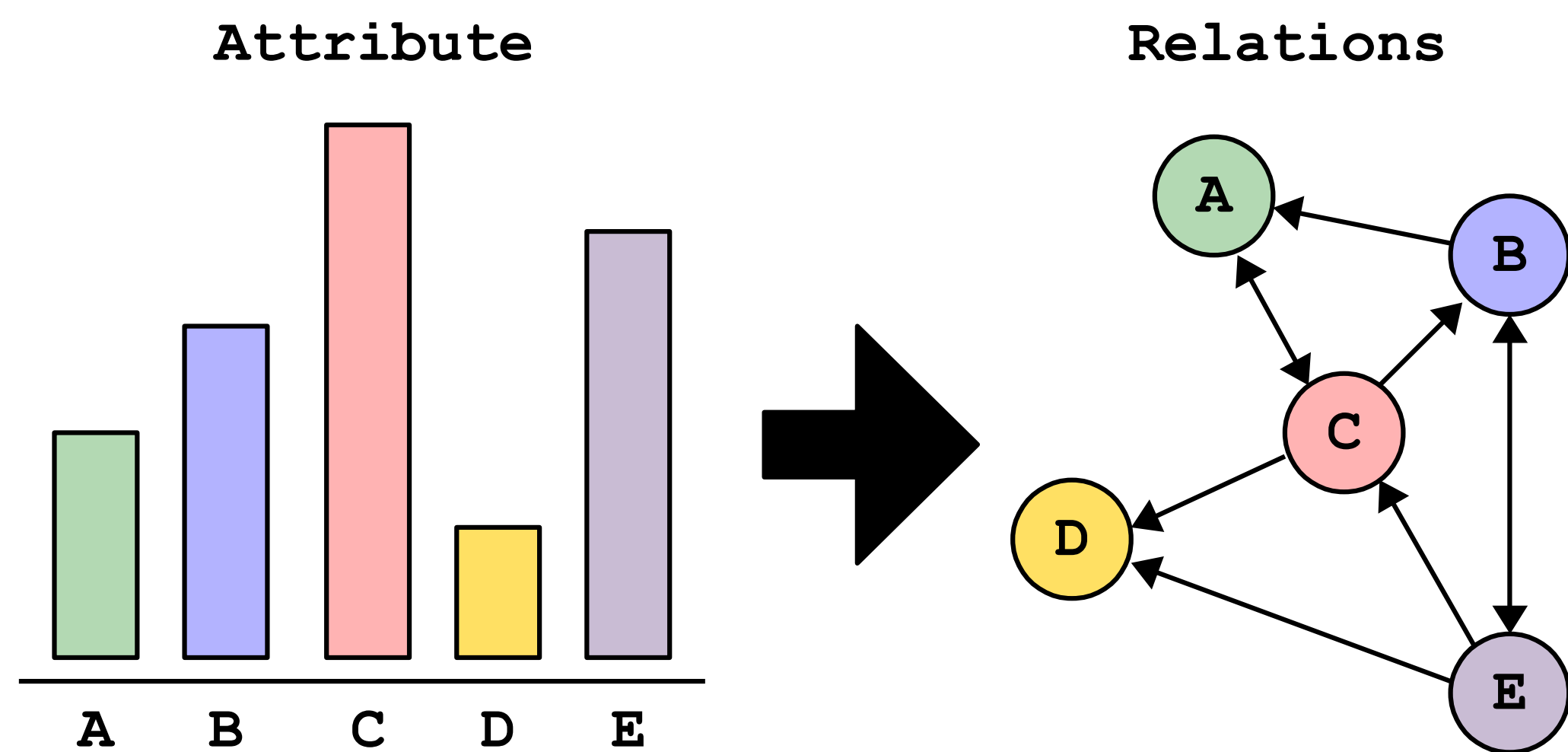


Existing Measures of Influence:

- **Floor amendments:** successfully passed by an MC (Sinclair, 1989; Smith, 1989; Weingast, 1992).
- **Reputation:** survey of legislative staffers (Hall, 1992).
- **Connectedness** (Fowler, 2006).
- **Weak ties (Cosponsorship)** (Kirkland, 2011).

A Relational Framework

Move beyond an individual-centered conceptualization to a set of relationships:

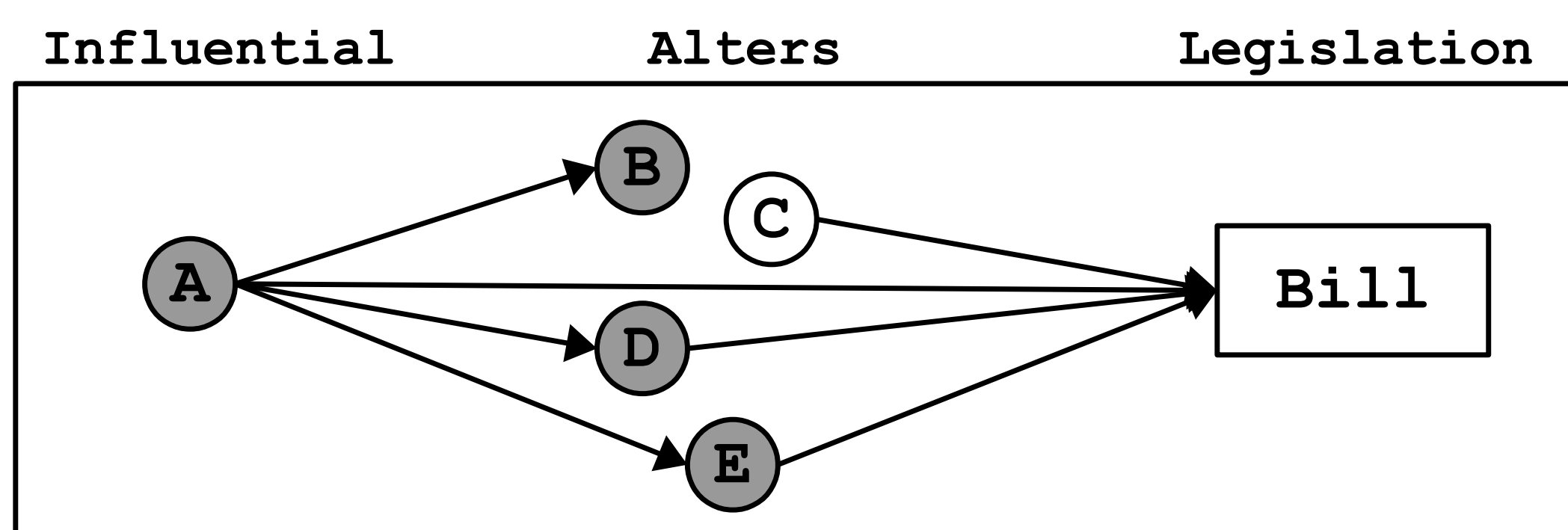


Characteristics of Influence:

- **Domain specific:** legislators hold more sway in some areas.
- **Directed:** Influence relations may be reciprocal or one-sided.



- **Failure Prone:** may not outweigh preferences.

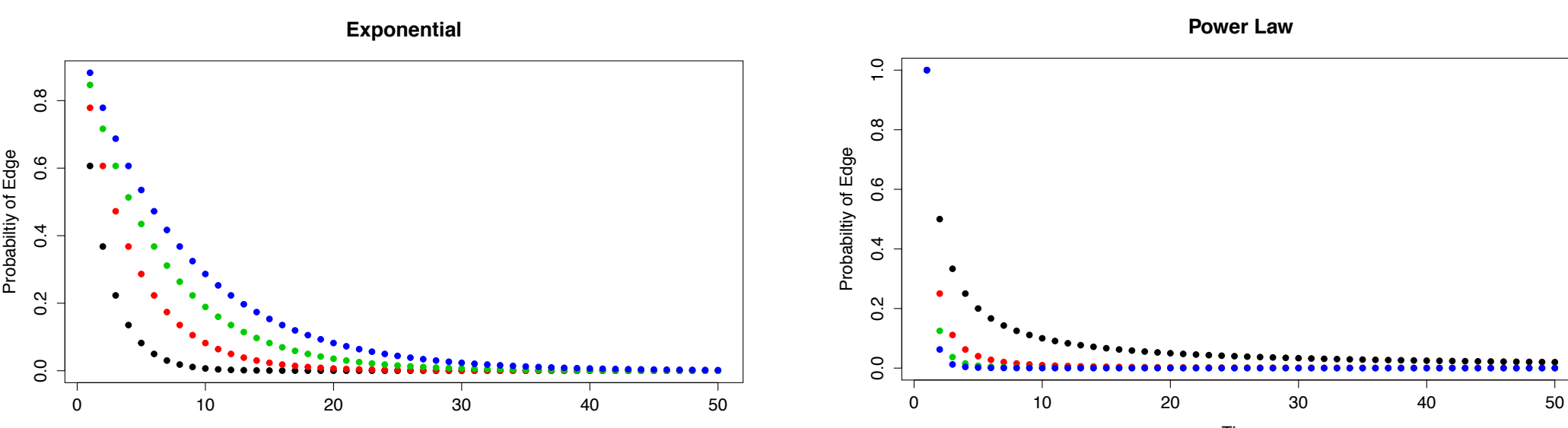


Measuring Influence Relationships

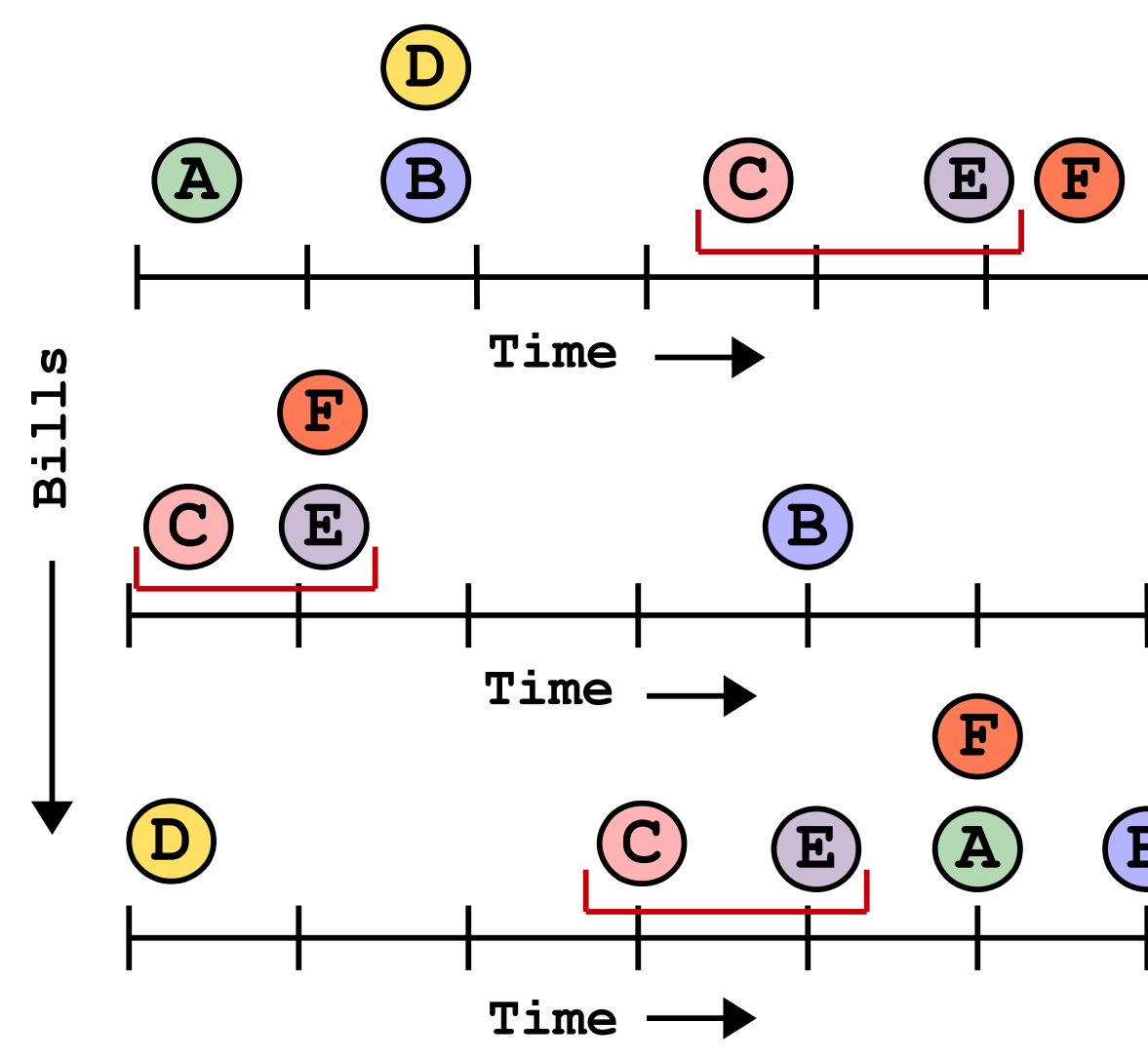
This study leverages temporal patterns in bill cosponsorship activity to infer a latent influence network using NETINF (Gomez Rodriguez et al., 2010).

- Cosponsorship of a bill results from cascade of interpersonal influence.
- Look for consistent temporal patterns in bill cosponsorship activity.
- Infer a latent influence network that maximizes the probability of observed cascades.

Under this model, we treat each sequence of bill cosponsorships as arising from an influence cascade. The model assumes that temporal distance in cascades follows a power-law or exponential distribution:



Bill Cosponsorship Delay



Temporal Cascades

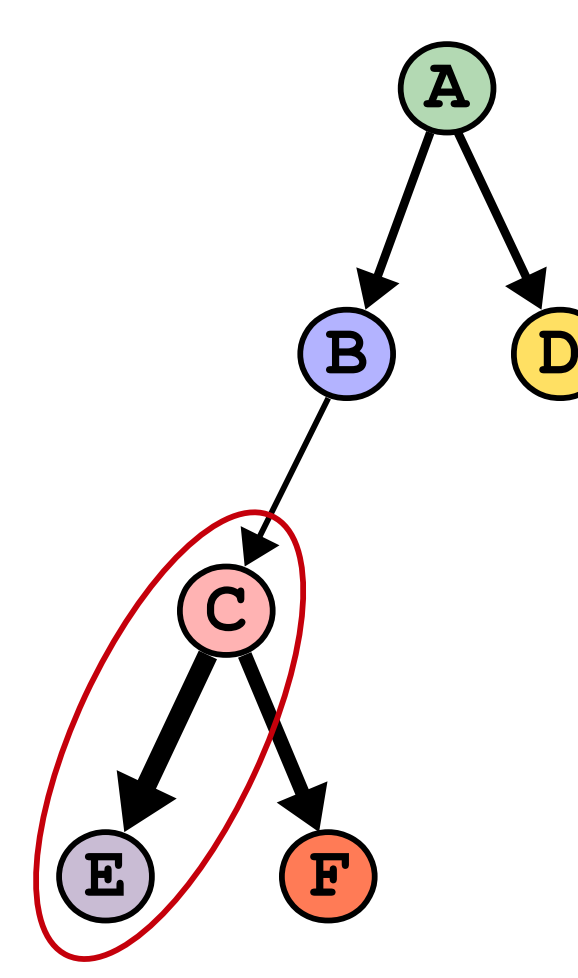
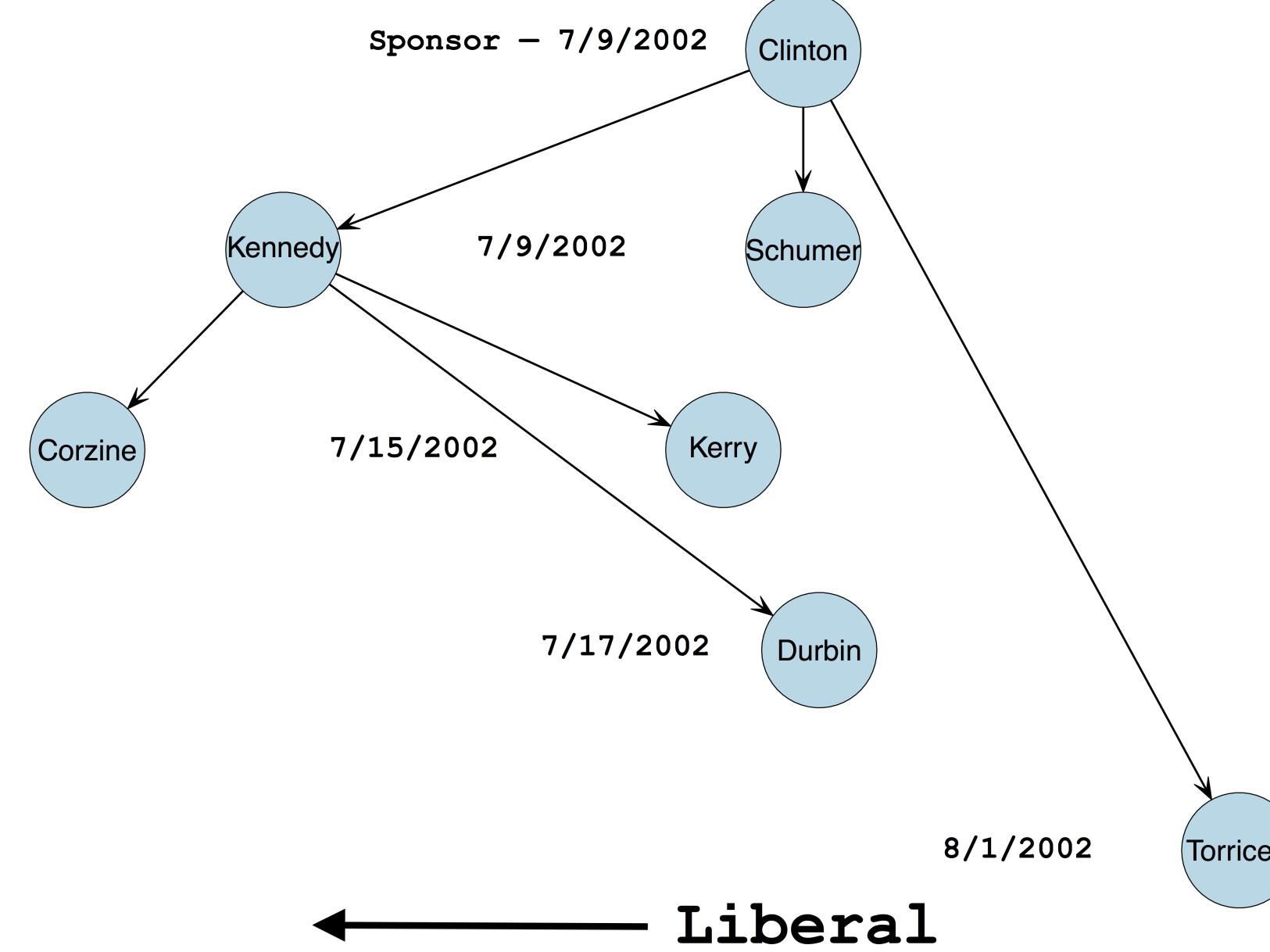


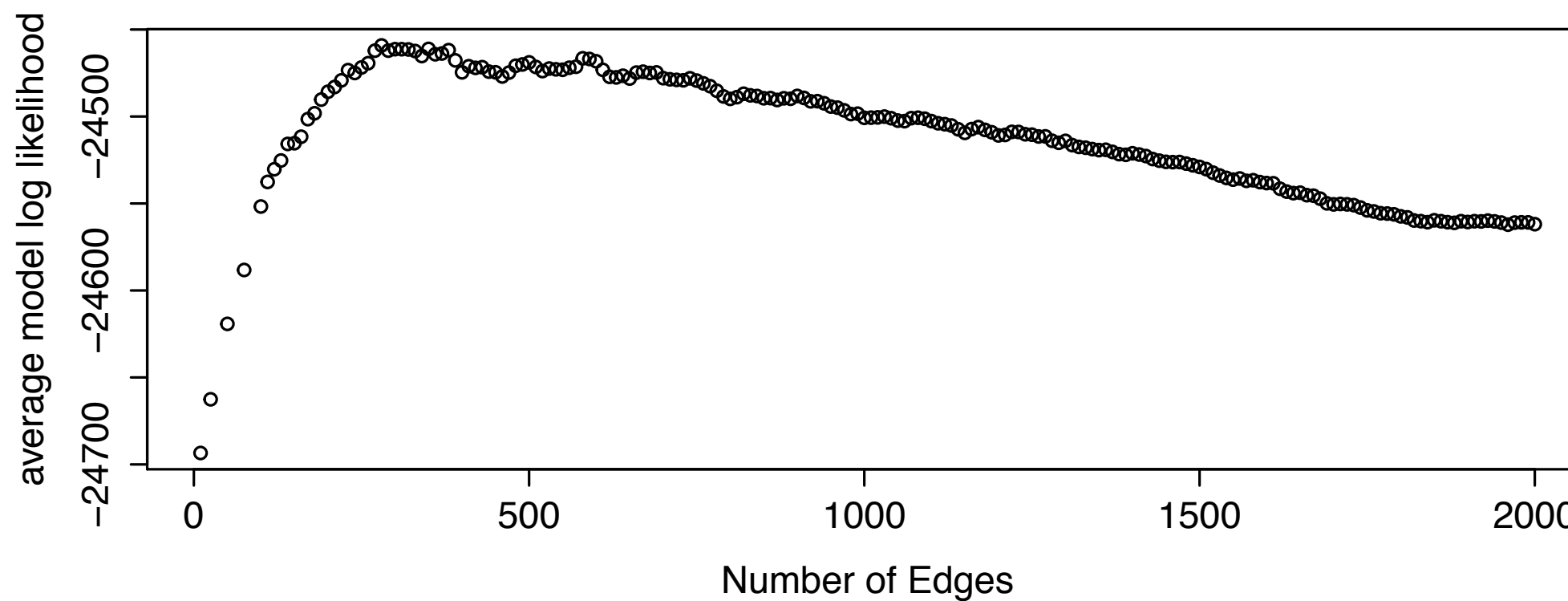
Figure: Most likely Influence cascade for S.2715, a bill to extend emergency unemployment benefits for victims of the 9/11 terrorist attacks.



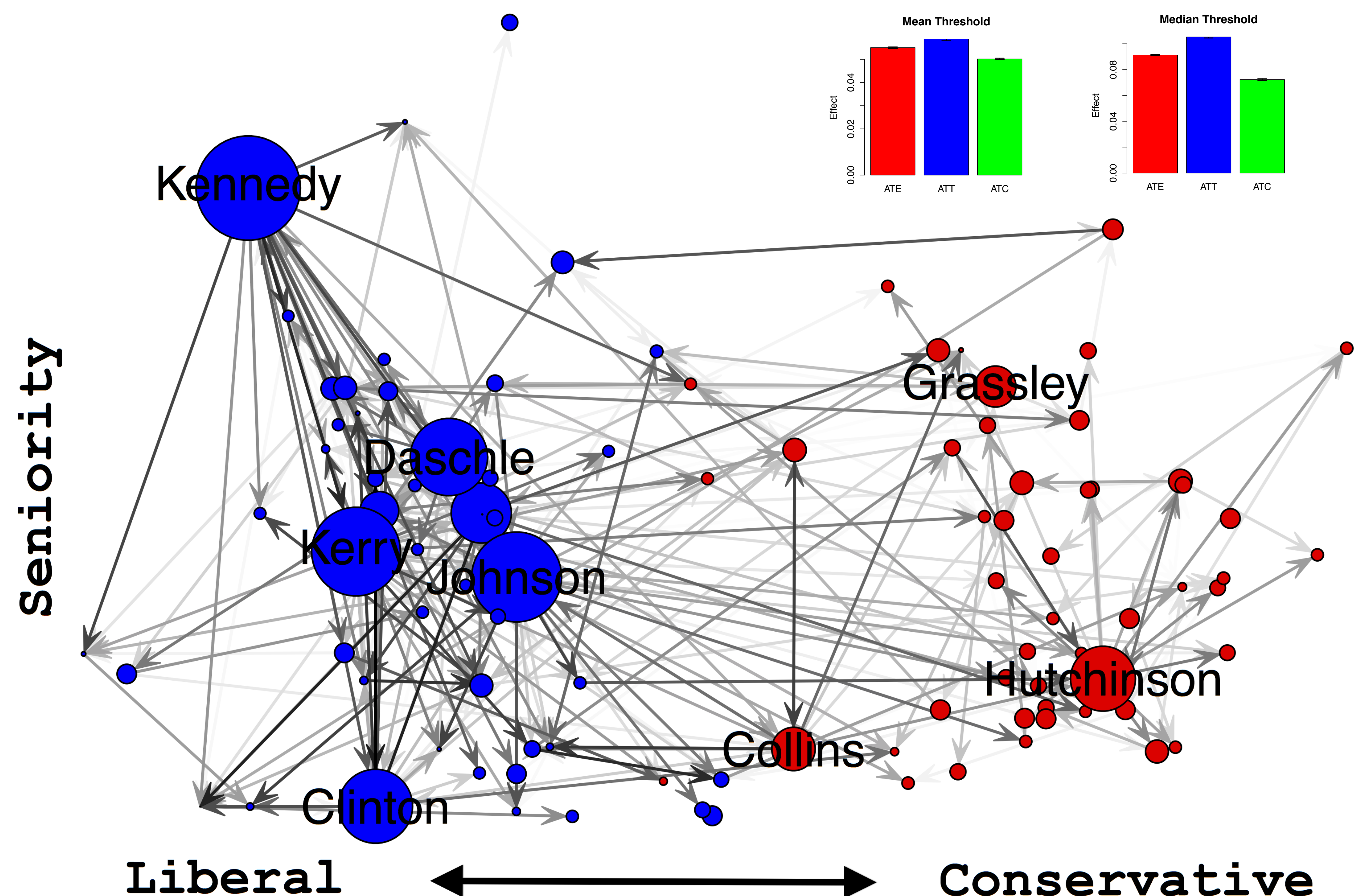
Model Selection

- Use inferred networks to predict cosponsorship timing.
- Use cross-validation with 10 splits for each congress.
- Use discrete event history model estimated with rare events logit (King and Zeng, 2001).
- Produces roughly 500x speedup vs. fully specified model.

Figure: Average held-out likelihood for 107th Senate: maximum at 298 edges.



Influence Network – 107th Senate

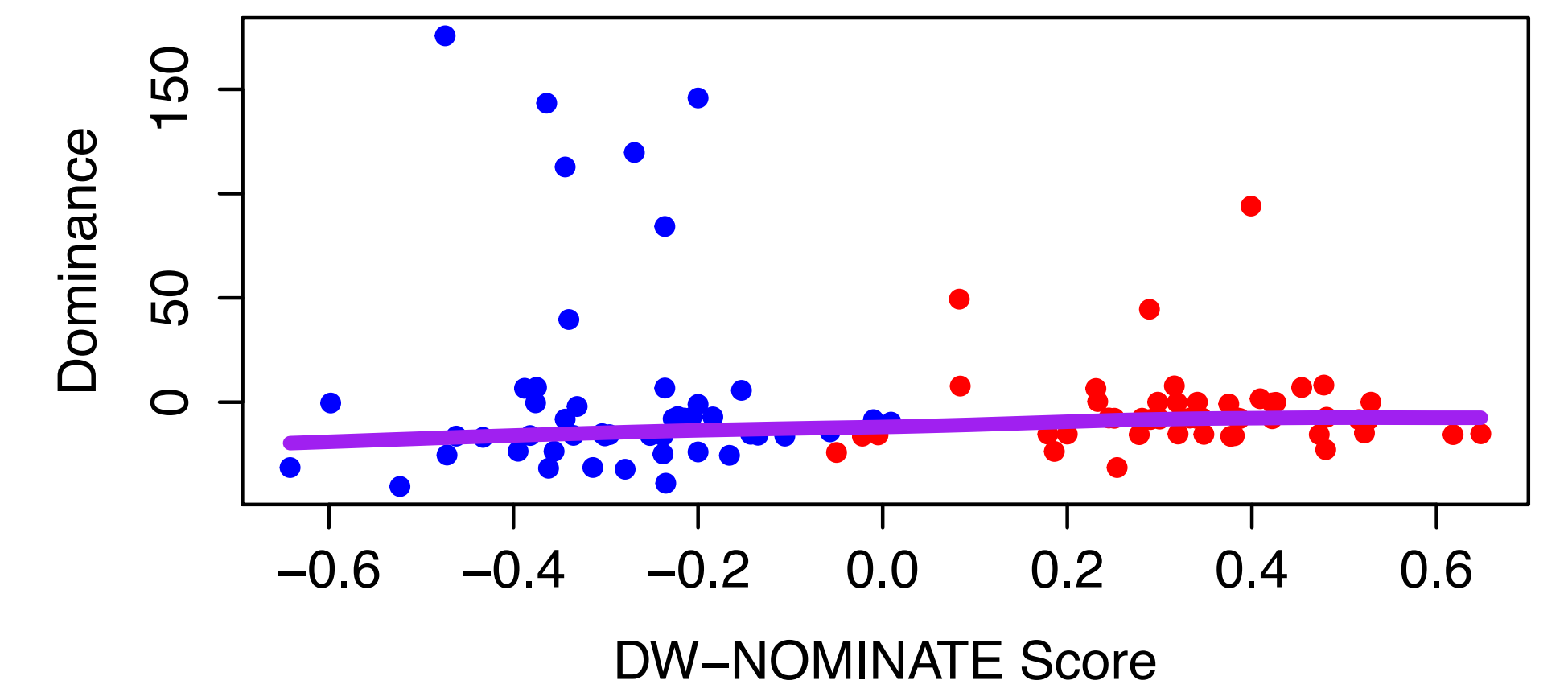


Measure Definition

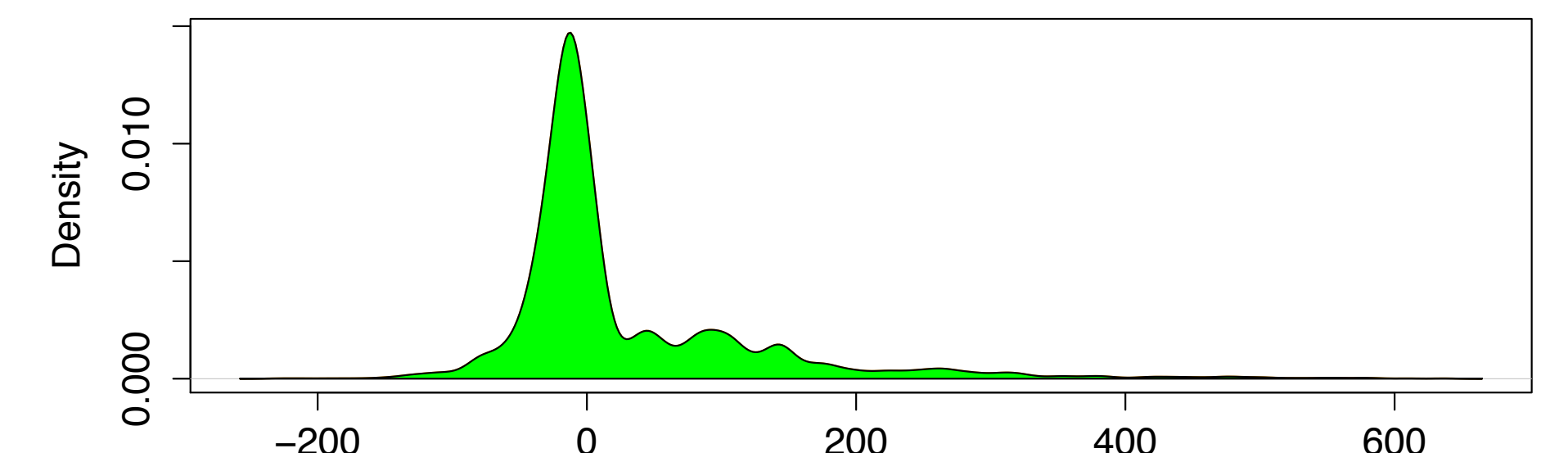
Let the *dominance* influence of a legislator be their (weighted) outdegree minus their indegree in the inferred influence network:

$$D_i = \sum_{j \neq i} l_{i,j} - l_{j,i} \quad \text{Where } l \text{ is the Influence Network} \quad (1)$$

Figure: Dominance influence scores for senators in the 107th Senate.

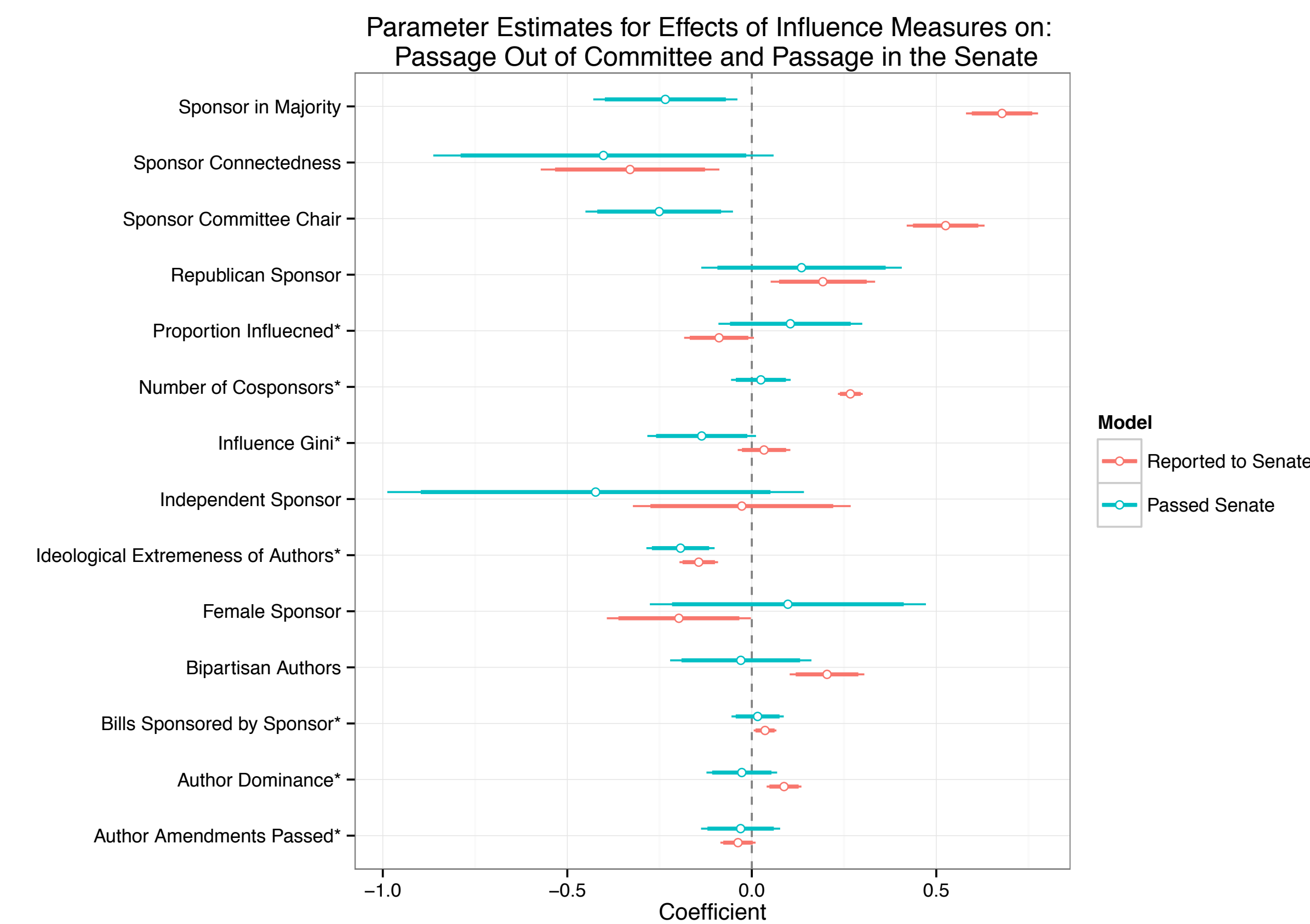


Density of aggregate bill author dominance for 107th Senate



Measure Comparison

Panel models with Senator, session and bill major topic (from Congressional Bills Project) fixed effects were estimated. Passage out of Senate sample subset to bills that passed committee.



Estimates of author dominance effect on bill passage out of committee using mean (33.71) and median (-1.588) thresholds. Exact matching on 9 variables with a bias correction for author floor amendments passed was used¹.

