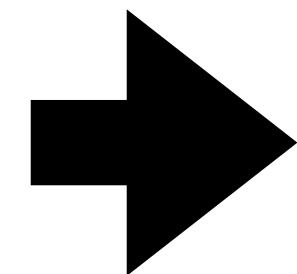


How Does a Technology Take Off? Stochastic Diffusion on Networks

Ye-eun Song

Technology: Spread vs Abandoned

- Some technologies take off, others fail to spread widely
 - A new “technology” is made
 - Early users appear, interact with potential users, leading to (possibly) more users
 - Some become popular (e.g., Python, Mathematica, Windows)
 - Some fail to spread widely (e.g., Blackberry OS, Windows Phone, MySpace)
- Some technologies are no longer widely used
 - Popular before, currently persist in legacy systems (e.g., COBOL, Perl)



Can these patterns be explained by simple stochastic models?

Questions

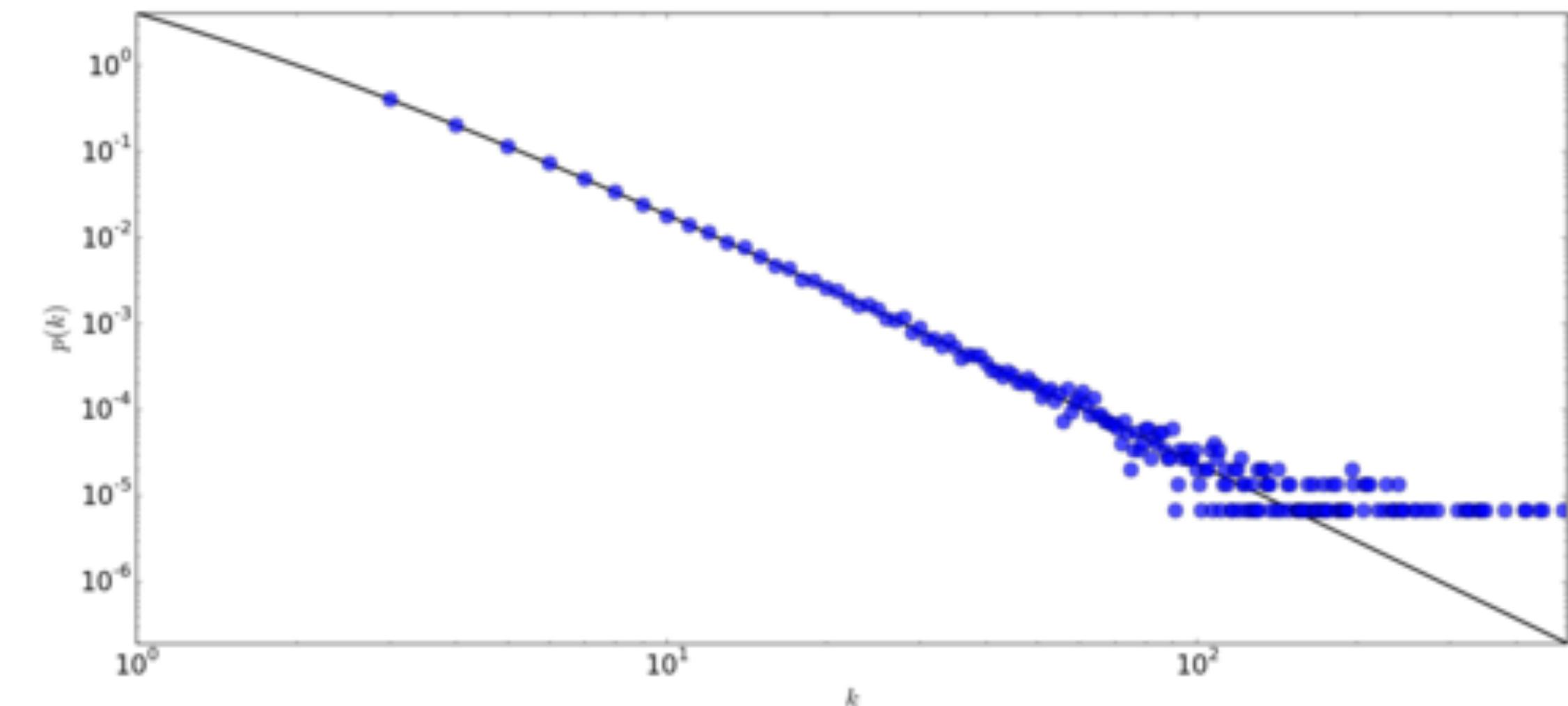
- When does a technology **spread widely** vs **die out**?
- How does **network structure** affect diffusion?
- Why do similar technologies show **very different outcomes**?
- How do **hubs** in a system affect diffusion?
- How does **interaction with users** affect outcomes?

SAR Model + Network Structure

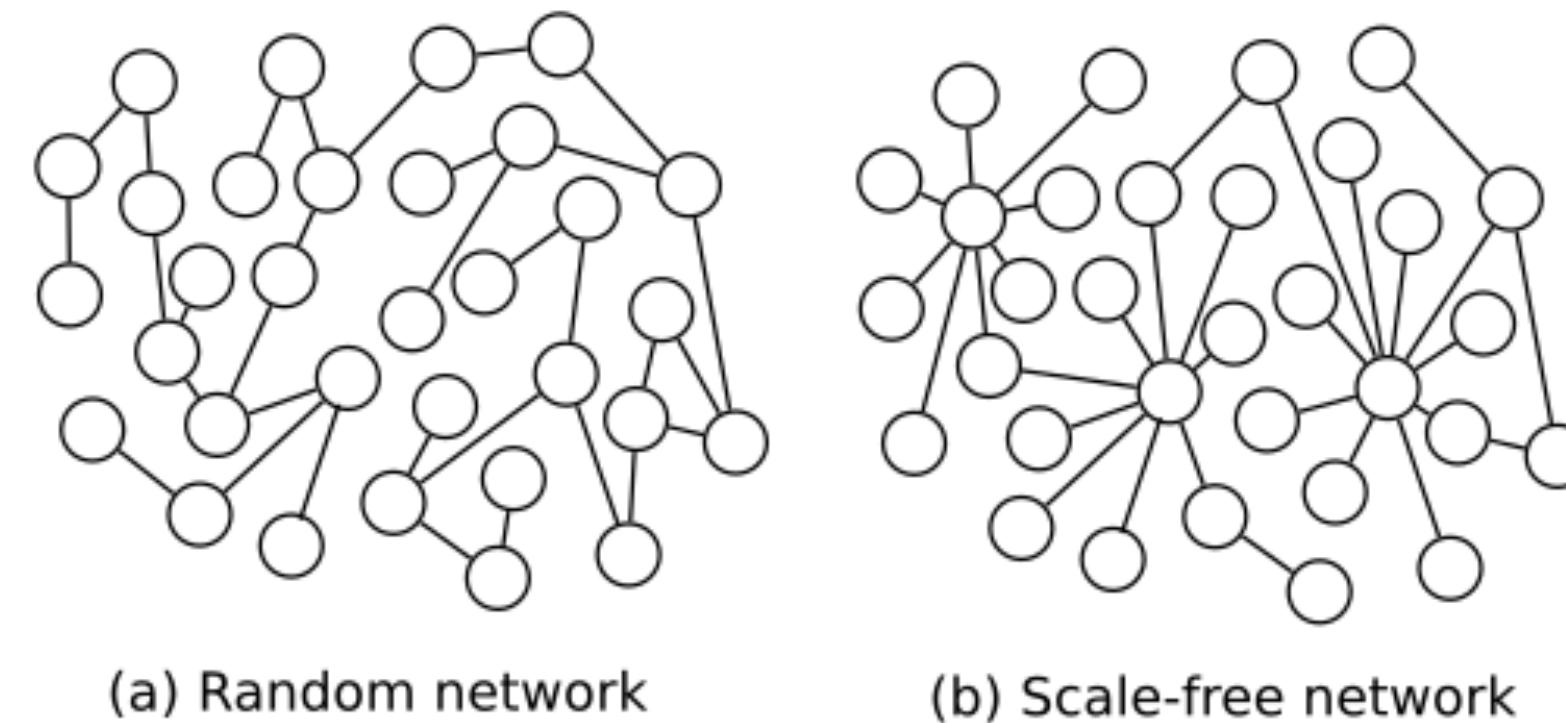
- Events are generated using the **Residence Time Algorithm**
- **User States**
 - **S**: Susceptible (non-active user)
 - **A**: Active
 - **R**: Abandoned (stopped using)
- **Transitions**
 - **S -> A**: adopts technology through interactions with active users
 - **A -> R**: stops actively using technology
 - **R -> A**: re-adoption of using the technology

SAR Model + Network Structure

- **Barabasi-Albert Model**
 - Follows a power law degree distribution
 - Preferential attachment: the rich get richer
- **Erdos-Renyi Network**
 - Random graph model
 - Baseline comparison model for BA Network



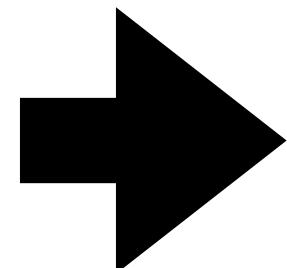
Degree distribution for a network with 150000 vertices and mean degree = 6 created using the Barabási-Albert model



HUBS!

Scope of “Technology” in this Project

- Product? (Canva, Figma, Zoom, ...)
- **Platform?** (Python, Docker, C++, ...)
- Paradigm? (Data Communication Protocol, Internet, AI, ...)



Platform-level technology (pre-AI era)

Experiment Setting

- $N = 10,000, A(0) = 10$
- Months = 96 (8 years)
- Transition rates

$$W = \underbrace{\beta \cdot (\# \text{ of S--A edges})}_{\text{adoption}} + \underbrace{\gamma \cdot A}_{\text{churn}} + \underbrace{\rho \cdot R}_{\text{re-adoption}}$$

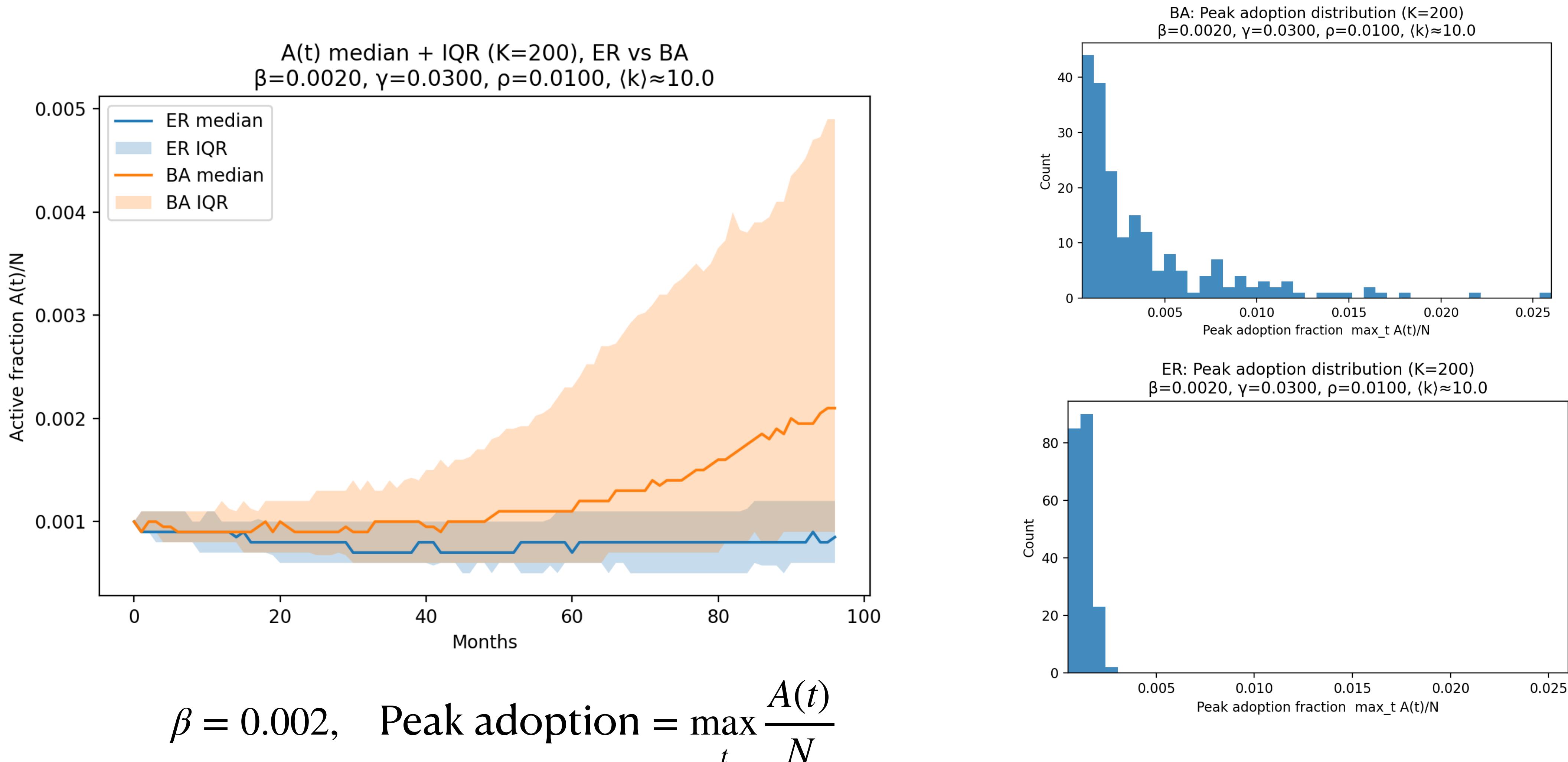
- Active state (A) : $\mathbb{E}[T_A] = \frac{1}{\gamma} = \frac{1}{0.03} \approx 33.3 \text{ months}$
- Removed state (R): $\mathbb{E}[T_R] = \frac{1}{\rho} = \frac{1}{0.01} = 100 \text{ months}$
- Ensemble statistics ($K = 200$ runs)
- Average degree $\langle k \rangle \approx 10$
- 2 network structures: Barabasi-Albert, Erdos-Renyi

Fixed parameters:
 $\gamma, \rho, \langle k \rangle, \text{network size}$

Varied parameters:
 $\beta, \text{network topology}$

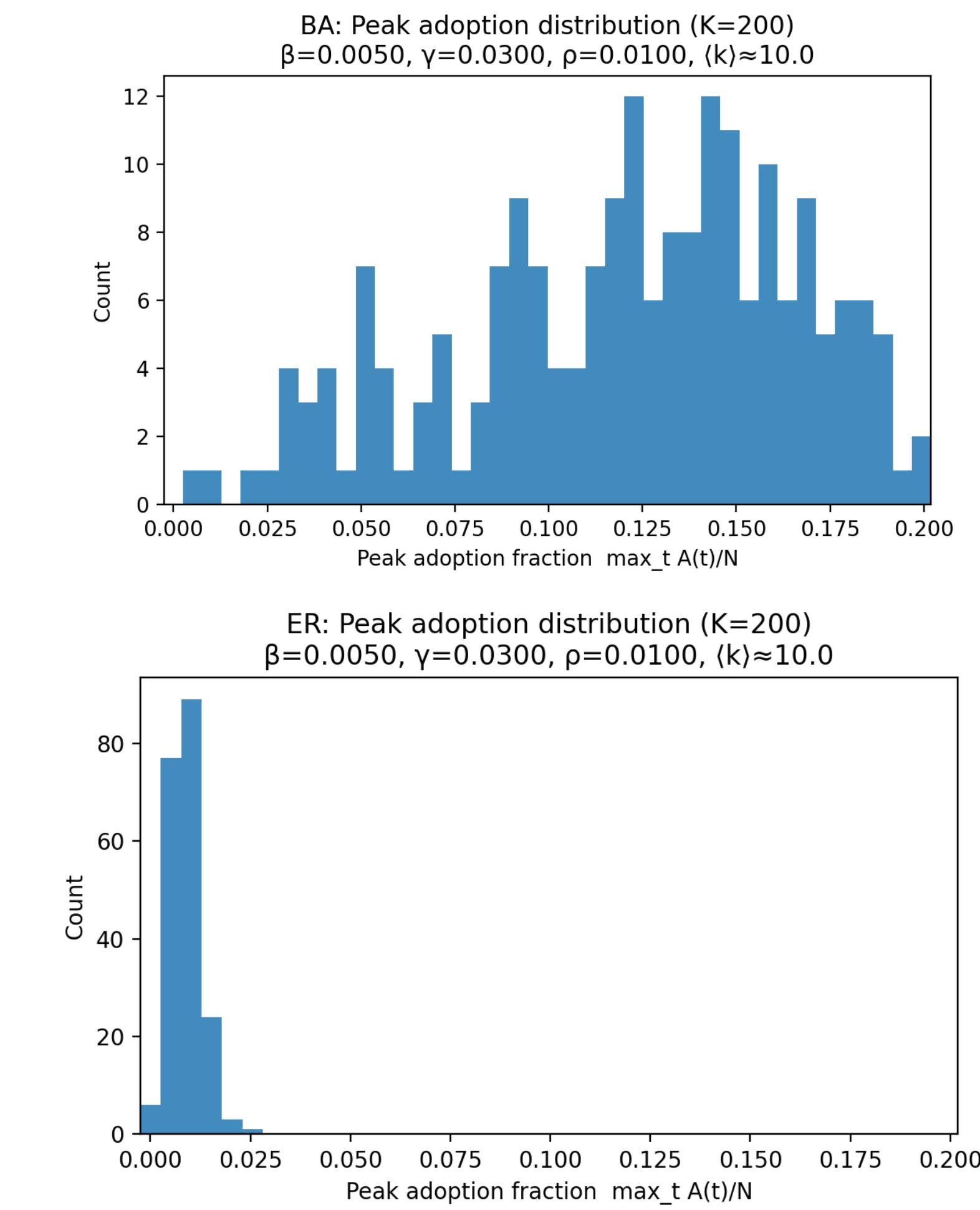
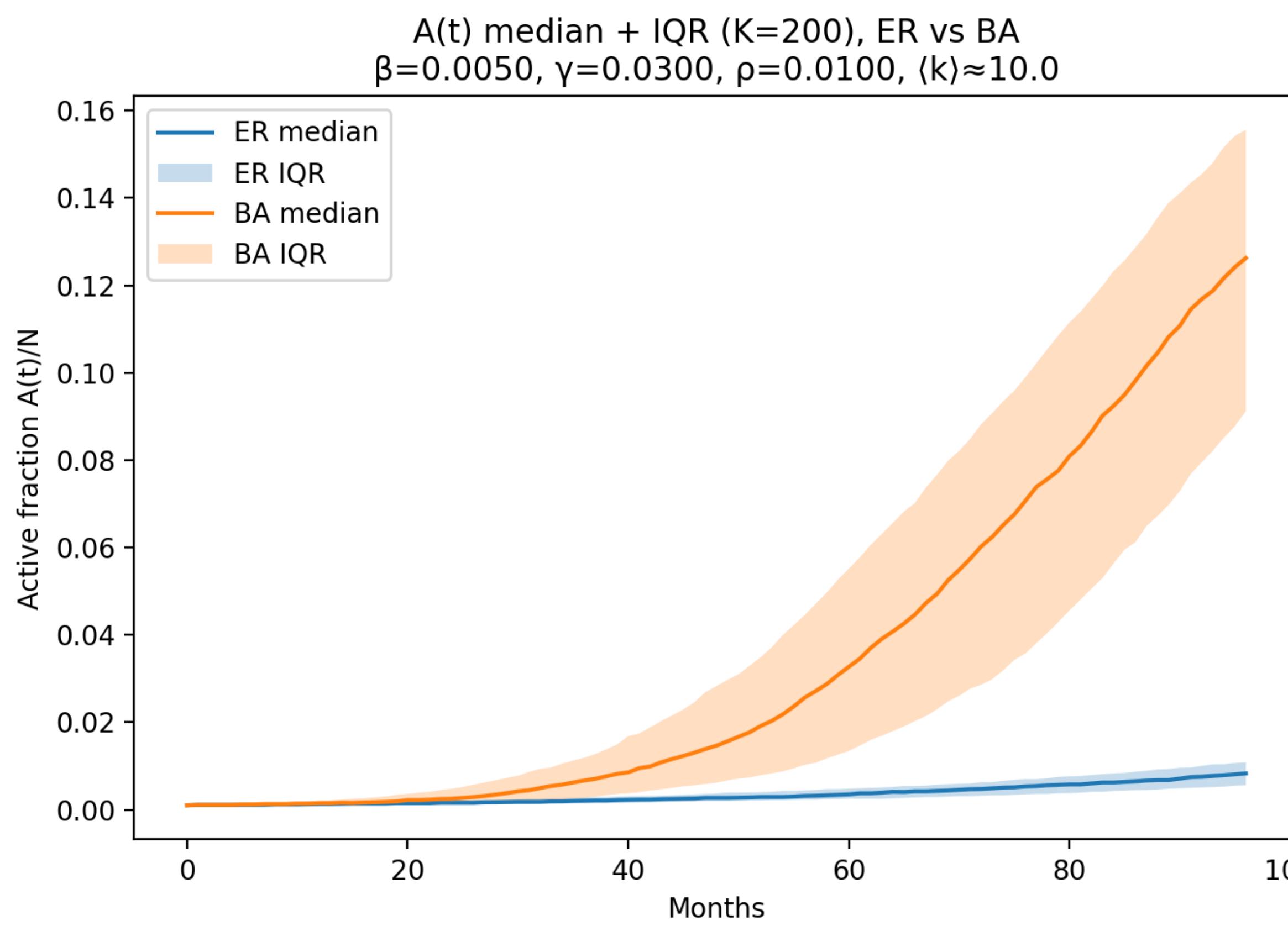
Results: Diffusion Trajectories

Stochastic Fluctuations and Network Affects



Results: Diffusion Trajectories

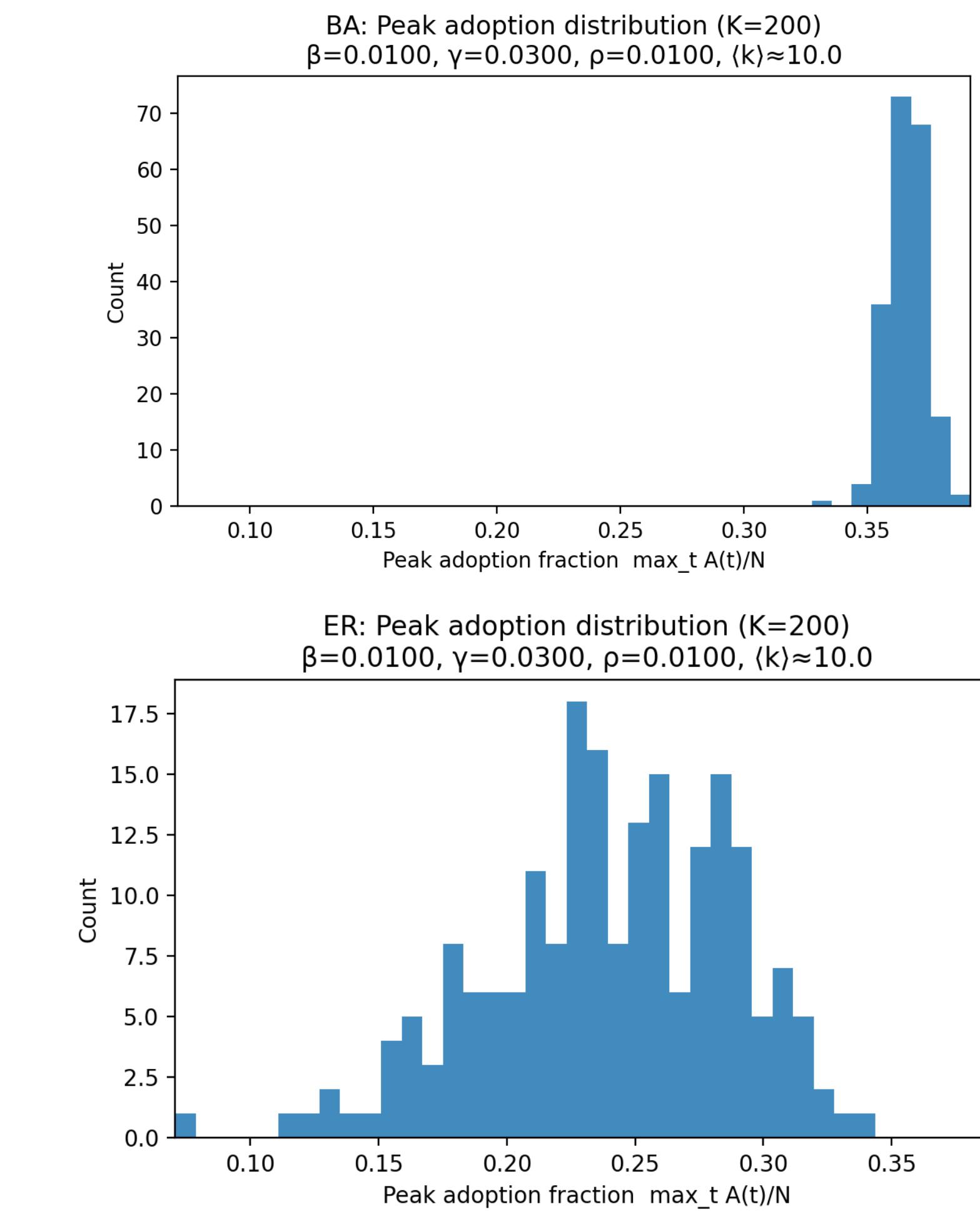
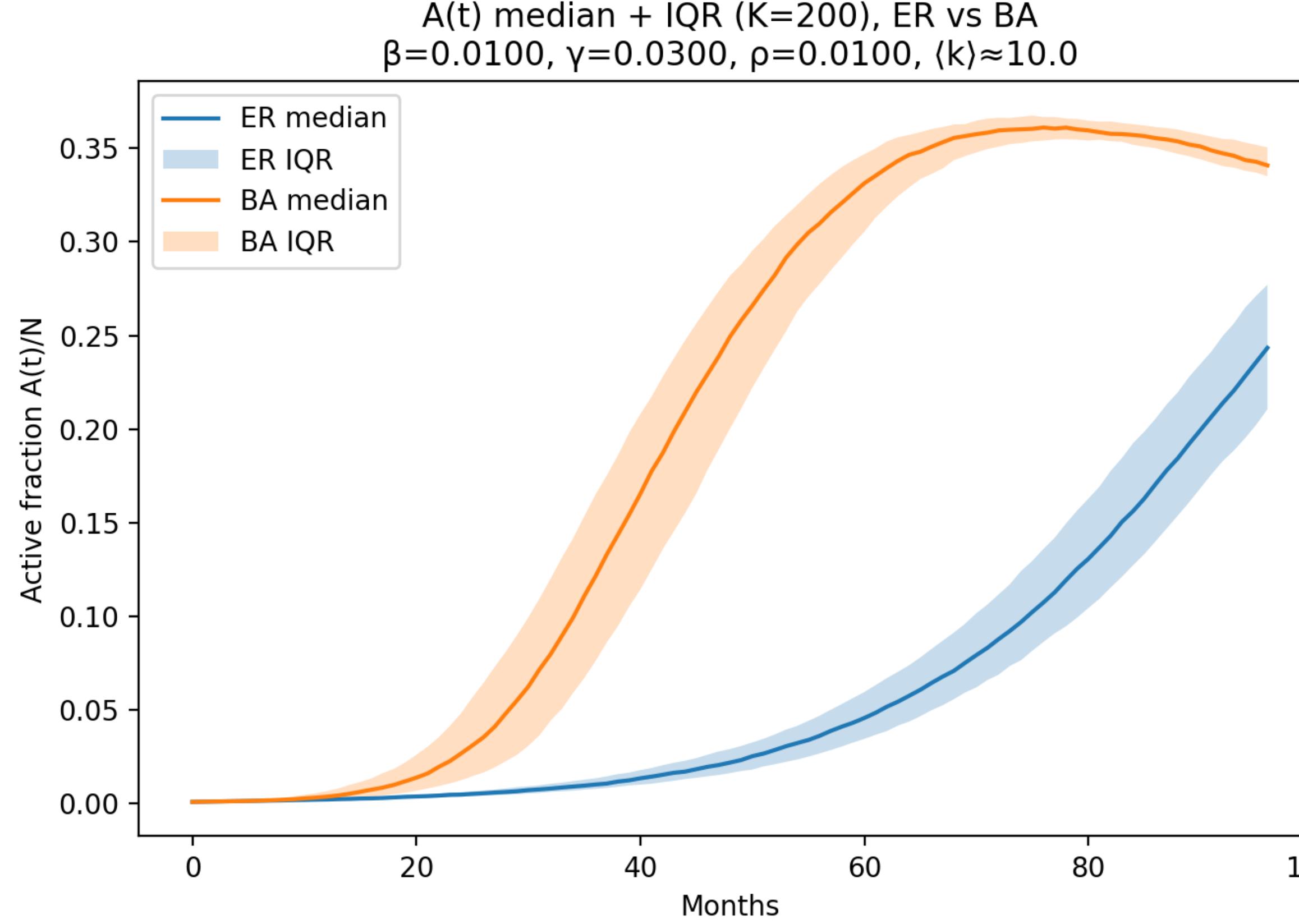
Stochastic Fluctuations and Network Affects



$$\beta = 0.005$$

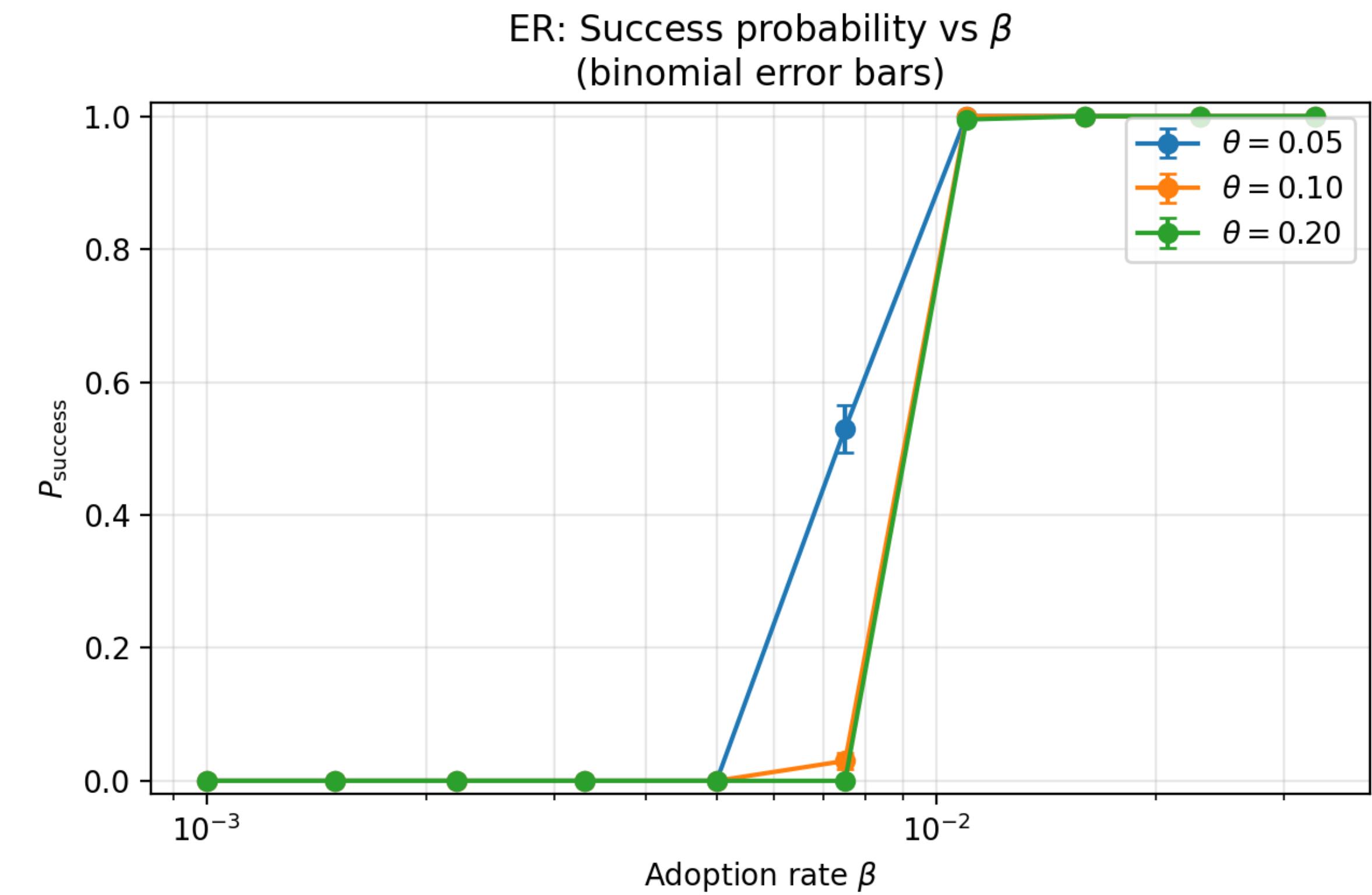
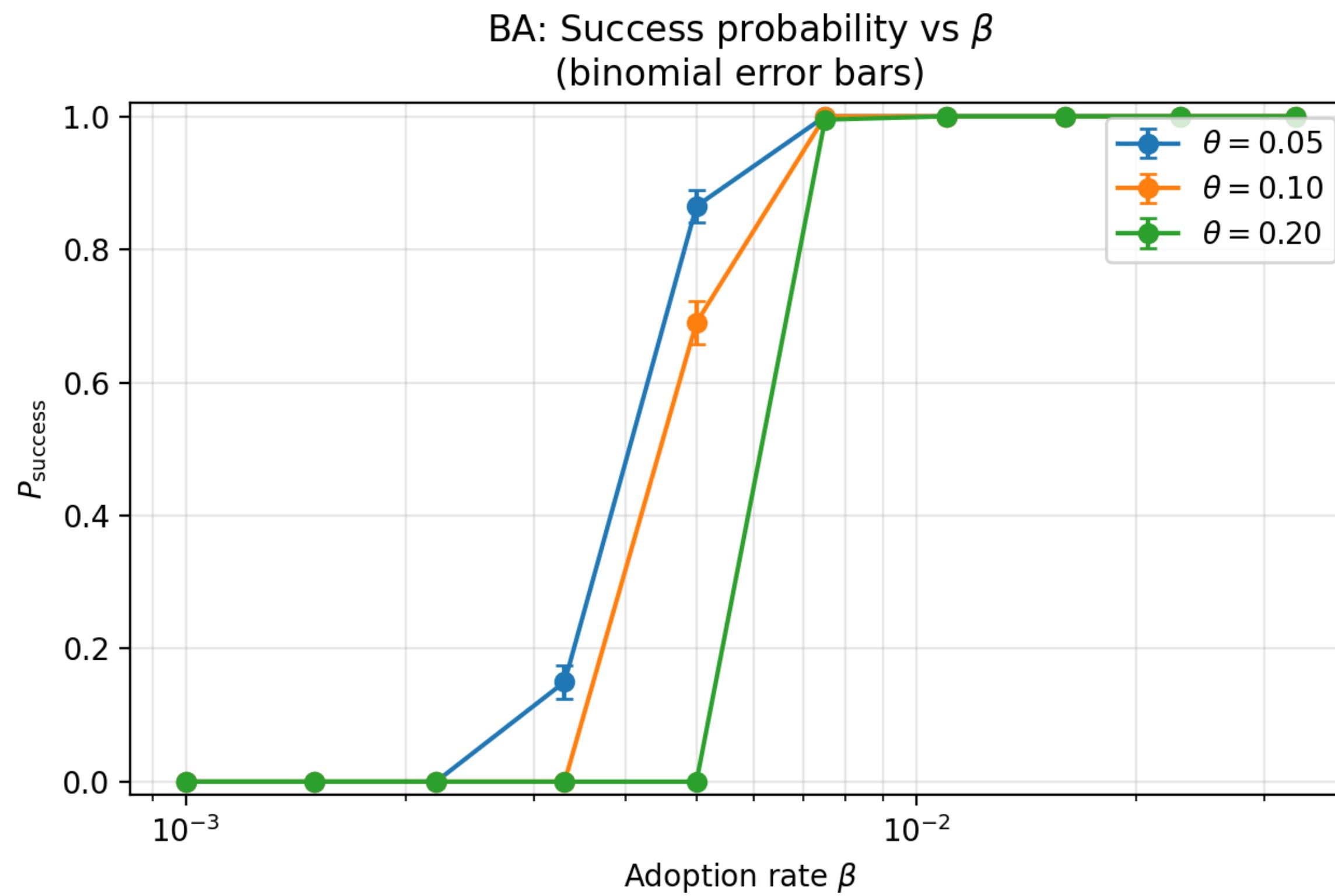
Results: Diffusion Trajectories

Stochastic Fluctuations and Network Affects



$$\beta = 0.01$$

Results: Success probability and β



$$P_{\text{success}}(\beta) = \mathbb{P}\left(\max_t \frac{A(t)}{N} \geq \theta\right)$$

Conclusion

- Simple stochastic models can reproduce:
 - Takeoff, failure, high variability
- Network structure strongly affects outcomes
- Early stochastic events matter, especially when the adoption rate is low
- Deterministic parameters alone are insufficient; random fluctuations play an essential role
- Future works: experiments on hubs, competition between technologies, effects of churns and re-adoption...