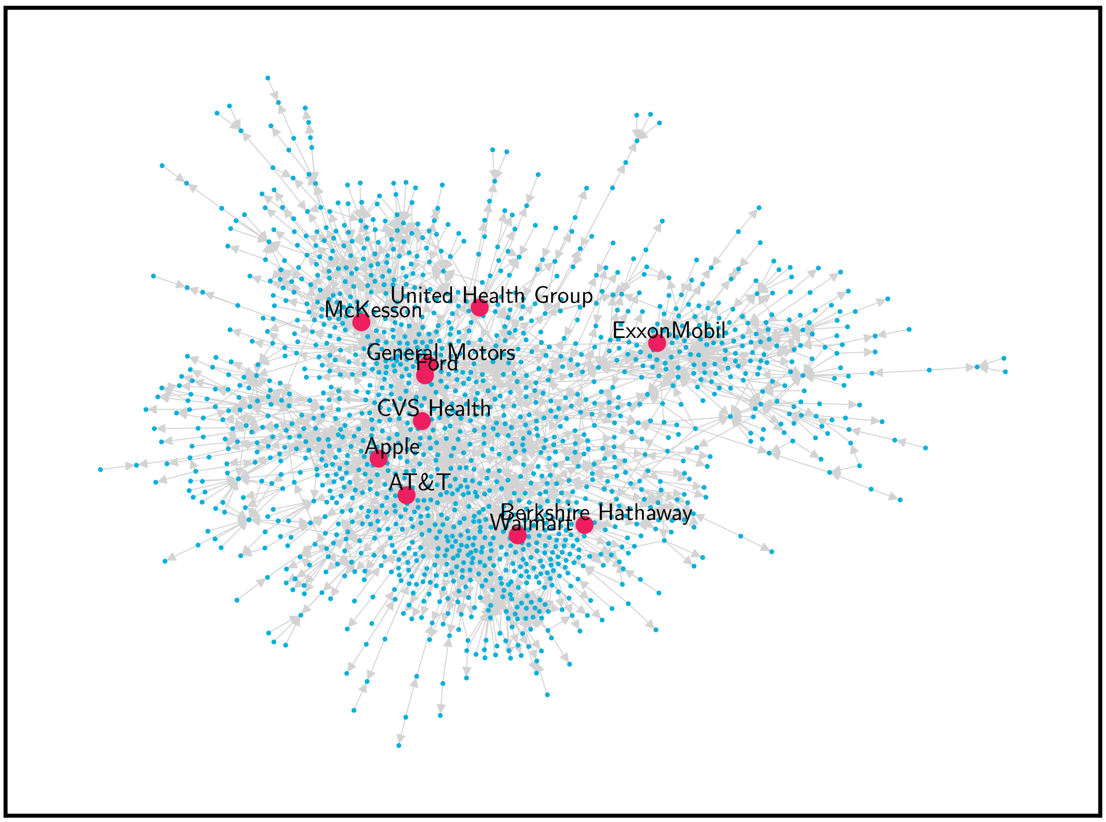
# Econometric Methods for Social Spillovers and Networks

*University of St. Gallen*

*October 1st to 9th, 2018*

**Course Description**

This course will provide an overview of econometric methods appropriate for the analysis of social and economic networks. Many social and economic activities are embedded in networks. Furthermore, datasets with natural graph theoretic (i.e., network) structure are increasingly available to researchers. We will review (i) how to describe, summarize and visually present network data and (ii) formal econometric models of network formation that admit heterogeneity, strategic behavior, and/or dynamics. The focus will be on the formal development of methods, but selected empirical examples will also be covered, as will methods of practical computation.



# Course Logistics

**Instructor:** Bryan Graham, Department of Economics, University of California – Berkeley

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**Time:** 8:15AM to 12:00PM, October 1,2,3,4,5 & 8

**Prerequisites:** The equivalent of a first year Ph.D. level sequence in econometrics. Specifically an understanding of probability and statistical inference at the level of Casella and Berger (1990, *Statistical Inference*), linear regression analysis at the level of Goldberger (1991, *A Course in Econometrics*) and some exposure to non-linear models (e.g., maximum likelihood, M-estimation, GMM). I will also assume a basic knowledge of applied linear/matrix algebra.

**Textbook:** Readings preceded by a [r] in the course outline are "required" (i.e., should ideally be read prior to class), while those preceded by a [b] are for "background" (i.e., may be useful for students interested in additional material or empirical applications). Students should consider purchasing the textbooks by Jackson (2006) and Newman (2010), but doing so is not necessary. The survey by Goldenberg et al. (2009) covers much of the technical literature in statistics and machine learning, but is now somewhat dated.

**Computation:** The bulk of class will be devoted to the formal development of the material, albeit with empirical illustrations as well as ample discussions of the various practicalities of implementation. However I do intend to reserve some class time for actual practice with computation. Computational examples will be done using Python. Python is a widely used general purpose programming language with good functionality for scientific computing. For those wishing to manage a Python environment on their personal computer, the Anaconda distribution, which is available for download at https://www.anaconda.com/distribution/, is a convenient way to get started. Some basic tutorials on installing and using Python, with a focus on economic applications, can be found online at `http://quant-econ.net`. Good books for learning Python, with some coverage of statistical applications, are Guttag (2013), VanderPlas (2017), and McKinney (2017). The code I will provide will execute properly in Python 3.6, which is (close to) the latest Python release. Graphviz is a free graph visualization program that is also useful (`http://www.graphviz.org/`).

# Course Outline

| Date | Topic | Readings |
|---|---|---|
| **Topic 1** | **Describing Networks** | [r] de Paula (2017); Jackson (2008); Jackson et al. (2017)<br>[b] Goldenberg et al. (2009) |
| | Examples of networks | [b] Atalay et al. (2011); Mizuno et al. (2014)<br>[b] Apicella et al. (2012) |
| | Small worlds | [b] Milgram (1967) |
| | Degree distributions | [b] Mitzenmacher (2004) |
| | Homophily | [b] McPherson et al. (2001) |
| | Triads | [b] Granovetter (1973); Jackson et al. (2012) |
| **Topic 2** | **(Shock) Propagation on Networks** | [r] Carvalho (2014)<br>[r] Alatas et al. (2016) |
| | | [b] Acemoglu et al. (2012, 2016)<br>[b] Banerjee et al. (2013) |
| **Topic 3** | **Nonparametrics: Graphons** | [r] Bickel & Chen (2009); Diaconis & Janson (2008) |
| | Estimation | [r] Chatterjee (2015); Zhang et al. (2017) |
| | Stochastic Block Model | [b] Daudin et al. (2008) |
| **Topic 4** | **Nonparametrics: Network Moments** | [r] Holland & Leinhardt (1976)<br>[b] Nowicki (1991) |
| | Theory | [r] Bickel et al. (2011) |
| | Computation | [r] Bhattacharya & Bickel (2015) |
| | $\beta$-Model | [r] Blitzstein & Diaconis (2011); Chatterjee et al. (2011) |
| **Topic 5** | **Models of Network Formation** | [r] Aronow et al. (2017)<br>[r] Graham (2017) |
| | Dyadic Link Formation | [b] König et al. (2017), Fafchamps & Gubert (2007) |
| | Dynamic Models | [r] Graham (2016) |
| | Strategic models | [r] Miyauchi (2016), Mele (2017) |
| **Topic 6** | **Peer Effects** | [r] Manski (1993), Graham (2008)<br>[r] Bramoullé et al. (2009), Calvó-Armengol et al. (2009) |
| | | [b] Blume et al. (2015), Jackson & Zenou (2015) |

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