

## Popularity Trajectories and Early Adolescent Substance Use

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(**PRO**moting **S**chool-Community **P**artnerships to **E**nhance **R**esiliency)

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### **Social Dynamics of Youth – NSF/HSD**

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### Outline:

- Inspirations
  - Social Net View
  - Coleman (of course!)
  - Introduce a new data source
- The PROSPER Peers Study
  - Basic sample & network structure
- Popularity Structure:
  - Macro stability across time & setting
  - Micro mobility within settings
  - Capturing Trajectories
- Popularity & Substance Use
  - Trajectory Models
- Conclusion

### Inspirations: Theory

“To speak of social life is to speak of the association between people – their associating in work and in play, in love and in war, to trade or to worship, to help or to hinder. It is in the social relations men establish that their interests find expression and their desires become realized.”

Peter M. Blau

*Exchange and Power in Social Life*, 1964

### Inspirations: Theory

We live in a connected world:

"If we ever get to the point of charting a whole city or a whole nation, we would have ... a picture of a vast solar system of intangible structures, powerfully influencing conduct, as gravitation does in space. Such an invisible structure underlies society and has its influence in determining the conduct of society as a whole."

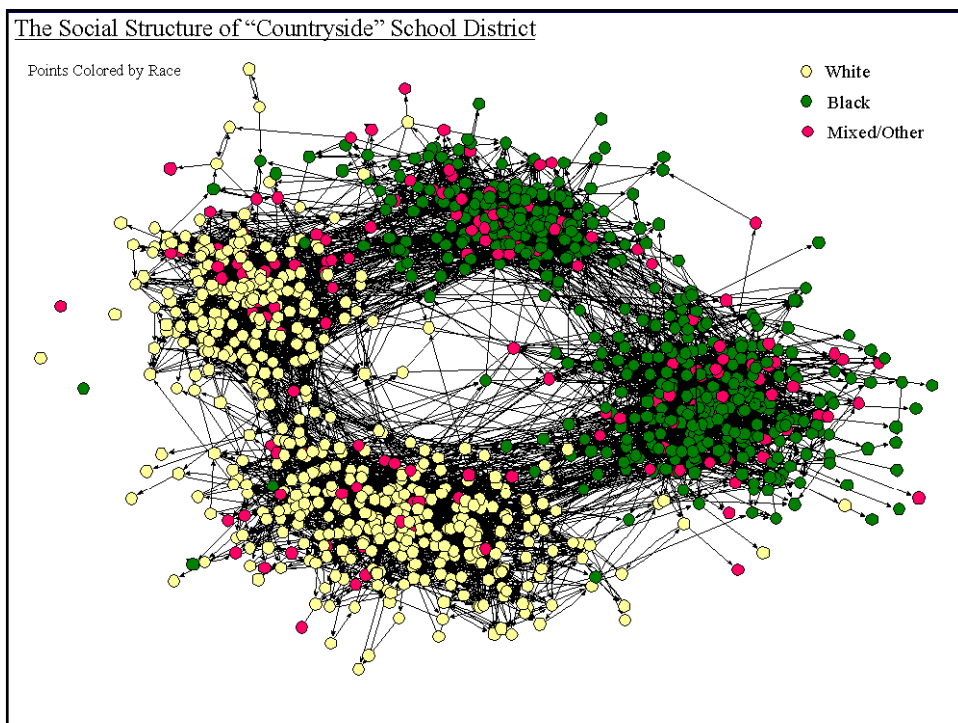
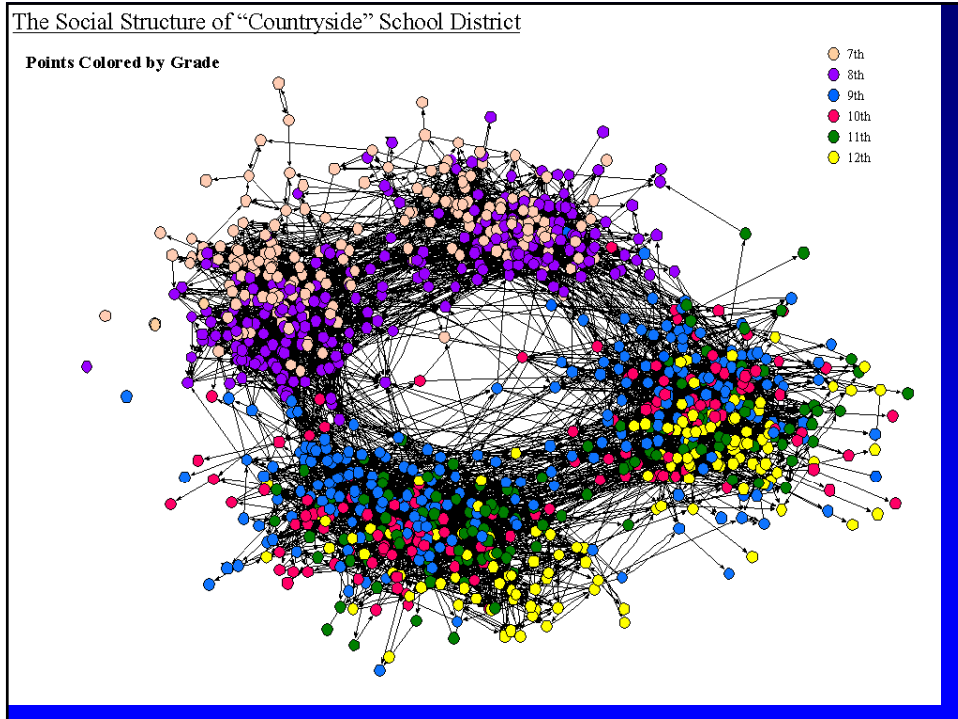
J.L. Moreno, *New York Times*, April 13, 1933

These patterns of connection form a *social space*, that can be seen in multiple contexts ranging from the development of science to high school social roles (and many many many more!)

### Inspirations: Theory

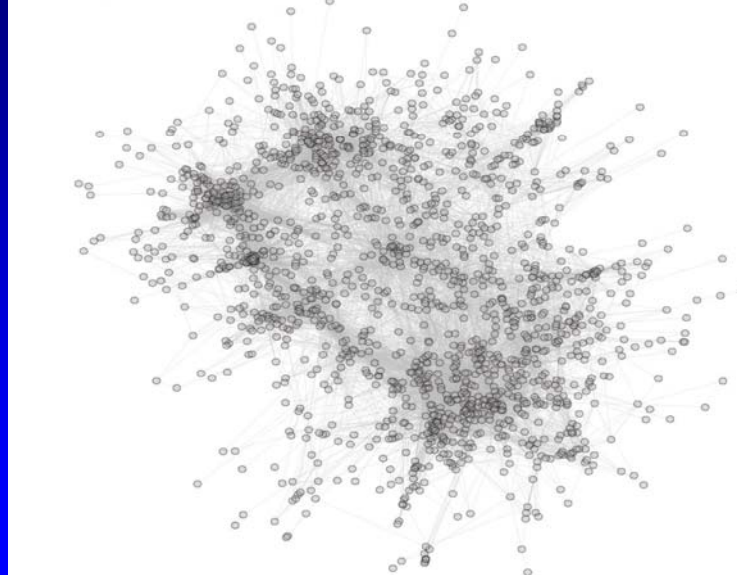
#### Schools as Networks





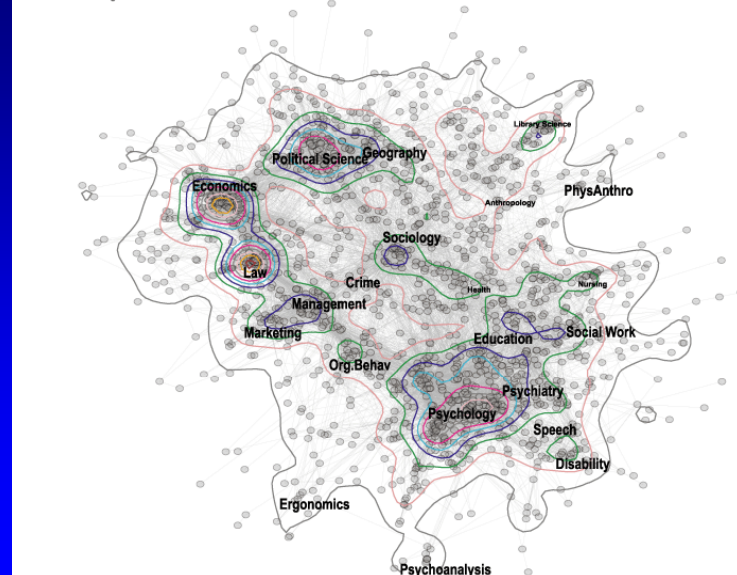
## Inspirations: Theory

The Discipline Structure of Social Science Journals  
Co-citation ties among 1657 Social Science Journals



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Co-citation ties among 1657 Social Science Journals



## Inspirations: Theory

“Science, carved into a host of detailed studies without any connection to each other no longer forms a cohesive whole.”

### - *The Division of Labor*

Standard “social problem” models often fail to produce an overarching image of social settings: particular moments are disconnected from the rest of social life (see Abbott 1997).

•But consider *The Adolescent Society* (1961) in contrast:

- Any particular element was really quite thin; bivariate associations, distributions, single-item measures.
- But taken together as a whole, Coleman produced a compelling vision of adolescent social life.
- Our broader goal is to capture this wider overview of how network features co-evolve with identity & behavior at the “adolescent society” level.

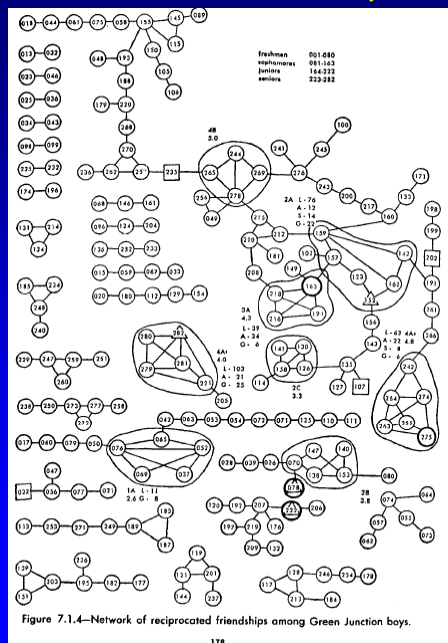
## Inspirations: Theory Schools as Social Systems

One of the earliest works to treat schools as lived social communities, focusing on the *relational structure* of the school.

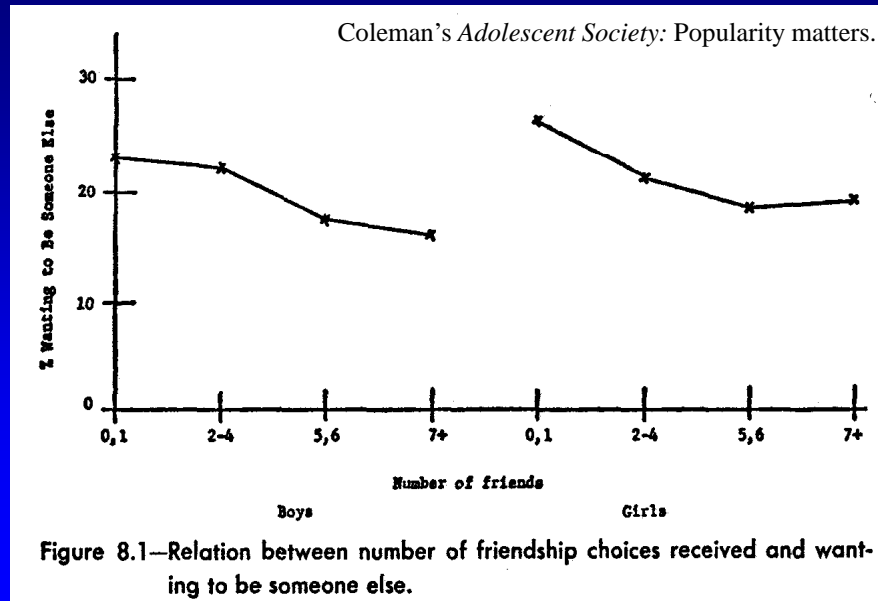
Individuals could be characterized by both their own involvement (ties) and characteristics of local groups (circled clusters at right).

Key distinction was one’s status location as a member of the “leading crowd.”

### Coleman’s *Adolescent Society*



### Inspirations: Theory



### Inspirations: Theory

We've known since at least *Elmtown's Youth* (1949) and certainly since *The Adolescent Society* that schools are significant sites for status struggles.

"Popularity", the "Leading Crowd," "Thugs," and so forth all signal *positions* that carry status implications.

Ethnographic work in schools suggests that youth are actively engaged in exploiting their behaviors and relations to position themselves within this game.

- Behaviors, dress, etc. signal a particular position
- Adolescents actively manage their social relations for status concerns.
- Relations *themselves* are of key interest to adolescents

The logic of practice in such fields suggest that position in the field should correspond to a relational structure and *distinct patterns* of how kids behavior changes over time.

#### Inspirations: Theory

Basic Insight: Patterns within the school network reflects social status, and youth behavior was closely linked to this status.

Here, we build on this idea by:

- 1) asking how status structures vary across settings
- 2) how position within a status structure changes over time
- 3) and how movement across this status structure affects substance-use behavior.

#### Inspirations: Theory

Status in youth culture is associated with adult activities that are in direct opposition to adult constraints/expectations. Thus:

**Main Effect:** we expect a positive association between substance use and popularity: in the cross-section, popular students should use substances (smoke, drink, drugs) more often than students who are less popular.

Trajectory Effects:

- a) To the degree that substance use confers status, *those gaining status* should start using at a higher rate. This is a “snowballing” effect of status, where the newly-ranked used more to shore up their status among peers.
- b) However, *loss of status* should lead to desperation and an attempt on the actors part to re-capture status, also leading to an increase in use, to a higher degree than (a).
- c) Similarly, high variability in status should create uncertainty that also leads to greater use.

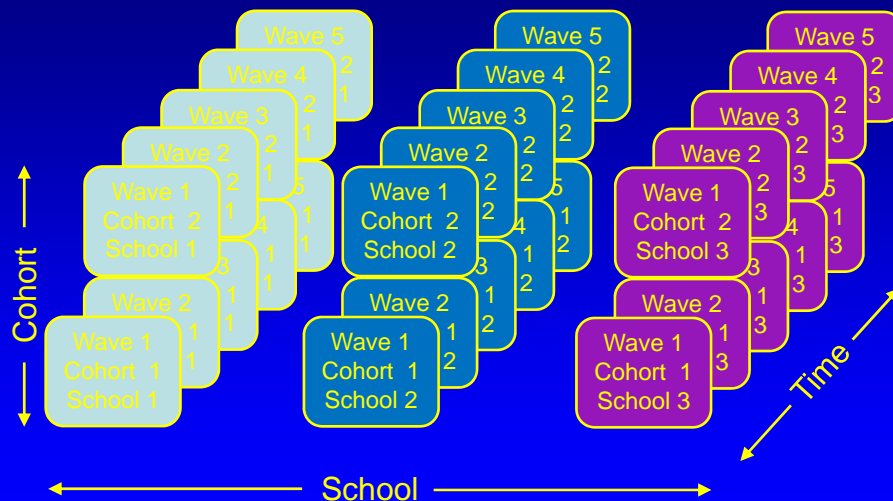


Inspirations: new data

## The PROSPER Study

- 27 towns, 2 grade cohorts, >11,000 students
  - Iowa & Pennsylvania, Small towns
  - 11,000+ Students
- Questionnaires assess friendships
  - Fall of 6<sup>th</sup> grade & Spring of 6<sup>th</sup>, 7<sup>th</sup>, 8<sup>th</sup>, & 9<sup>th</sup>...
  - ...plan to continue following *through high school*
- Experimental School-level Program targeting substance use
- Lead investigators of base Prosper Program:
  - Dick Spoth, Cleve Redmond, Iowa State Univ
  - Mark Greenberg, Mark Feinberg, Penn State Univ
- Networks component added w. funding from W.T.Grant & NIDA

## PROSPER Peers Research Design



## The PROSPER Peer Network Data

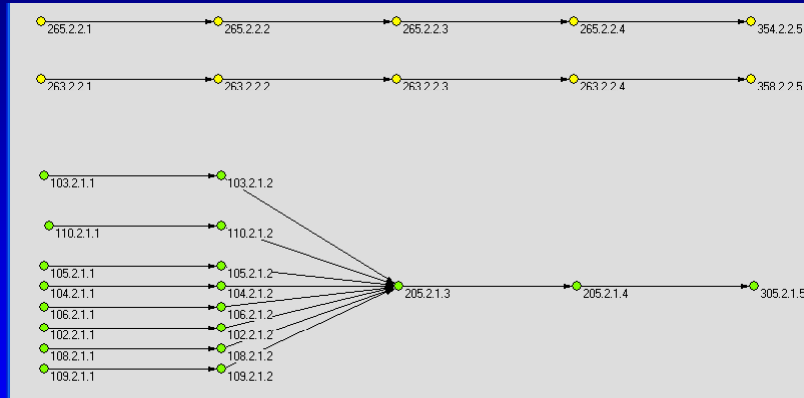
**Who are your best and closest friends in your grade?**

First name	Last Name (or if you don't know their last name, . . . )	How often do you "hang out" with this person outside of school, (without adults around)? 1) Never . . . 5) Almost Every Day
<b>YOUR BEST FRIEND or FRIENDS</b>		
<b>OTHER CLOSE FRIENDS</b>		

## PROSPER Peers Data Quality

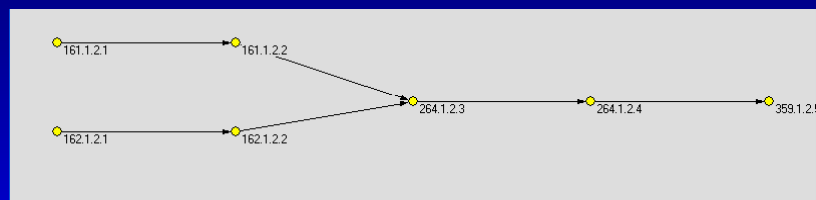
- Response rate: 87.2%
- Valid nomination data, Overall: 81.9%
  - Of respondents: 93.9%
  - Isolates: 3.4%
- Name matching, Overall: 79.3% - 88.5%
  - Out of school: ~7% (low, 6<sup>th</sup>), ~21% (high, 9<sup>th</sup>)
  - Matched, of within school: ~96% (91% - 98%)
- Reciprocation rate
  - Overall, above chance: 48.3%,
  - 1<sup>st</sup> choice: 76%; 1<sup>st</sup> choice, 4+ noms: 85%

## Mix of School Transitions

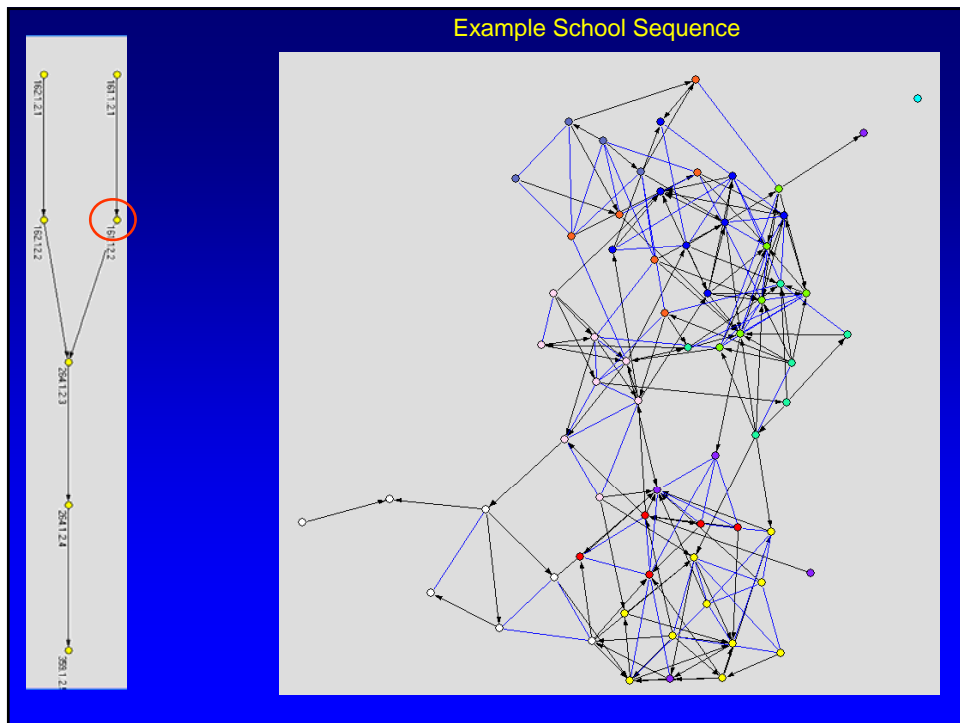
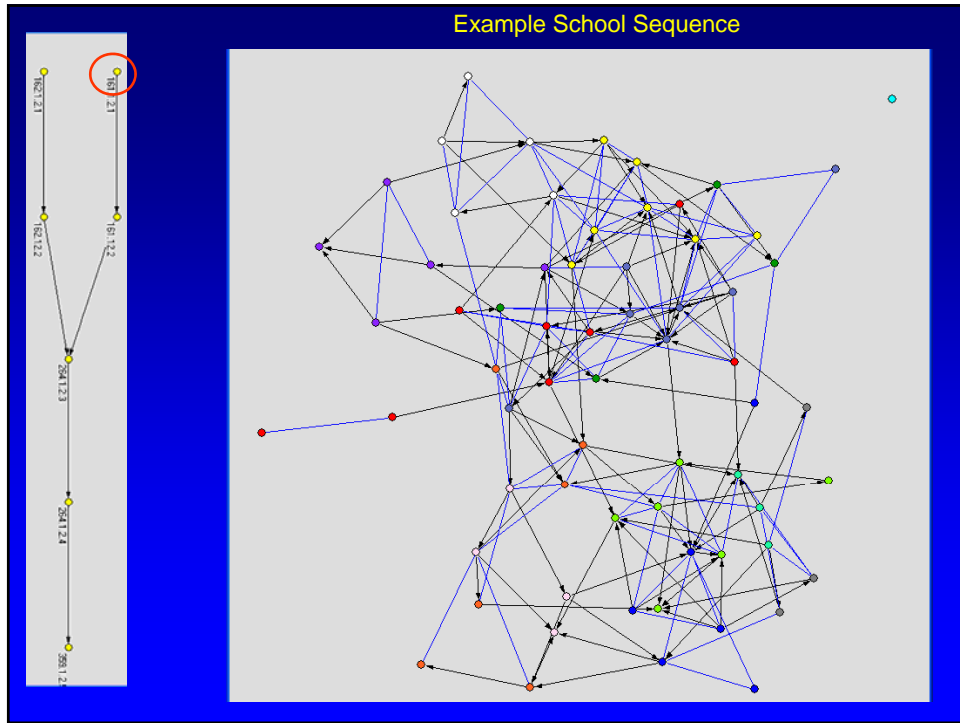


Elem grades → Middle School → High School

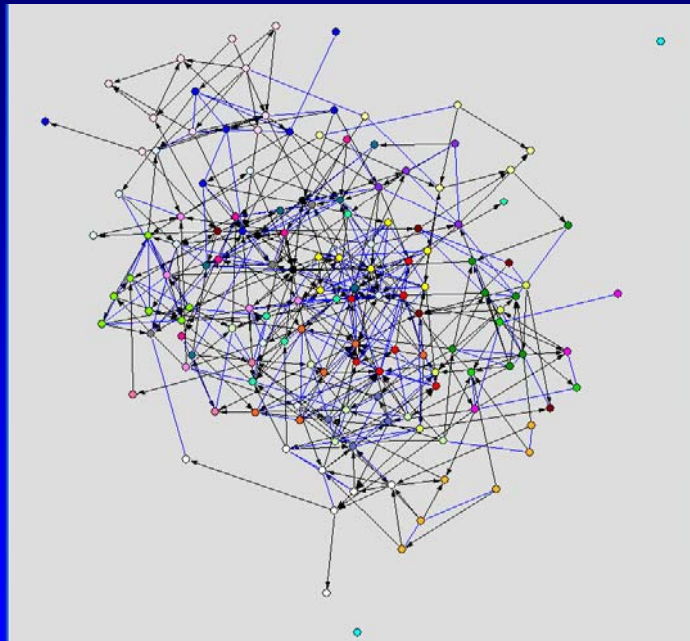
## Mix of School Transitions



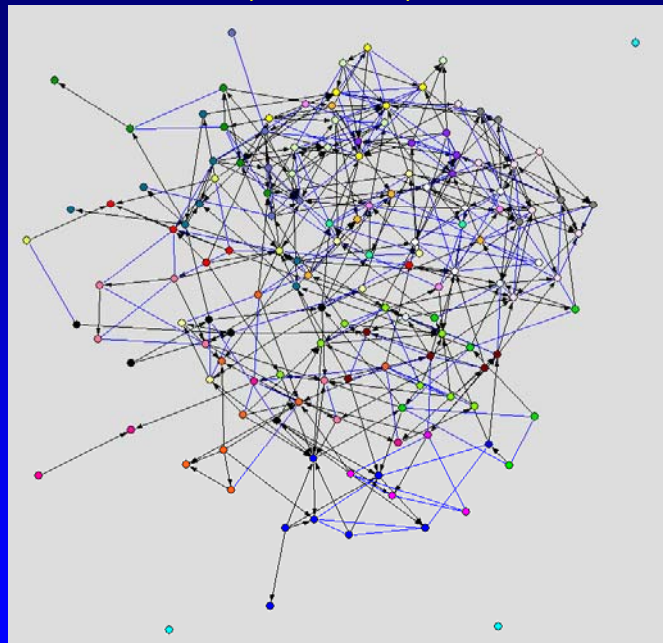
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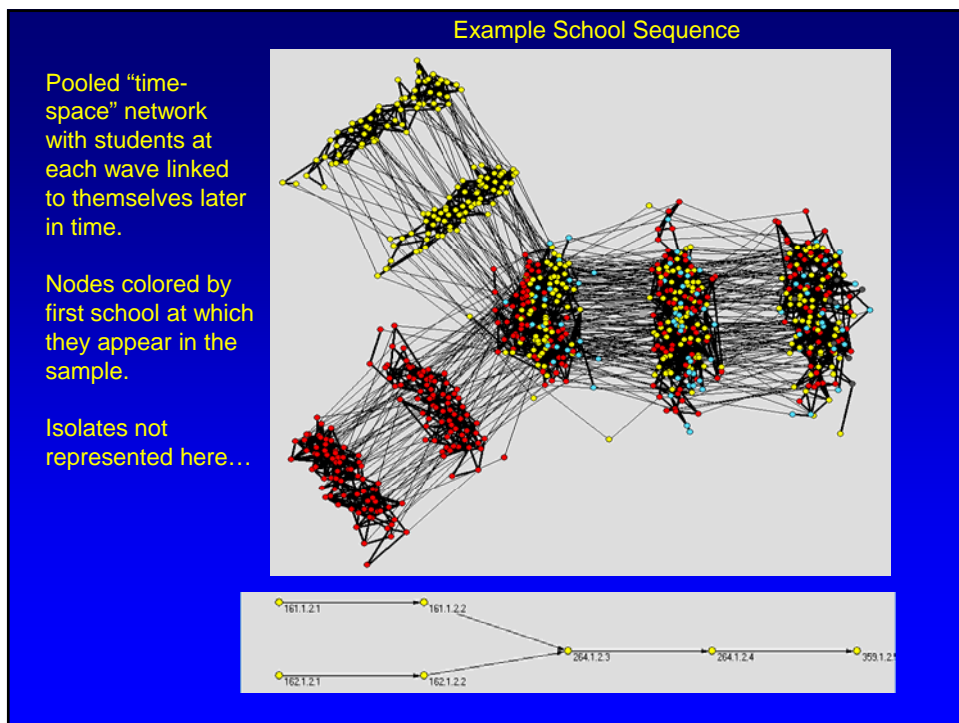
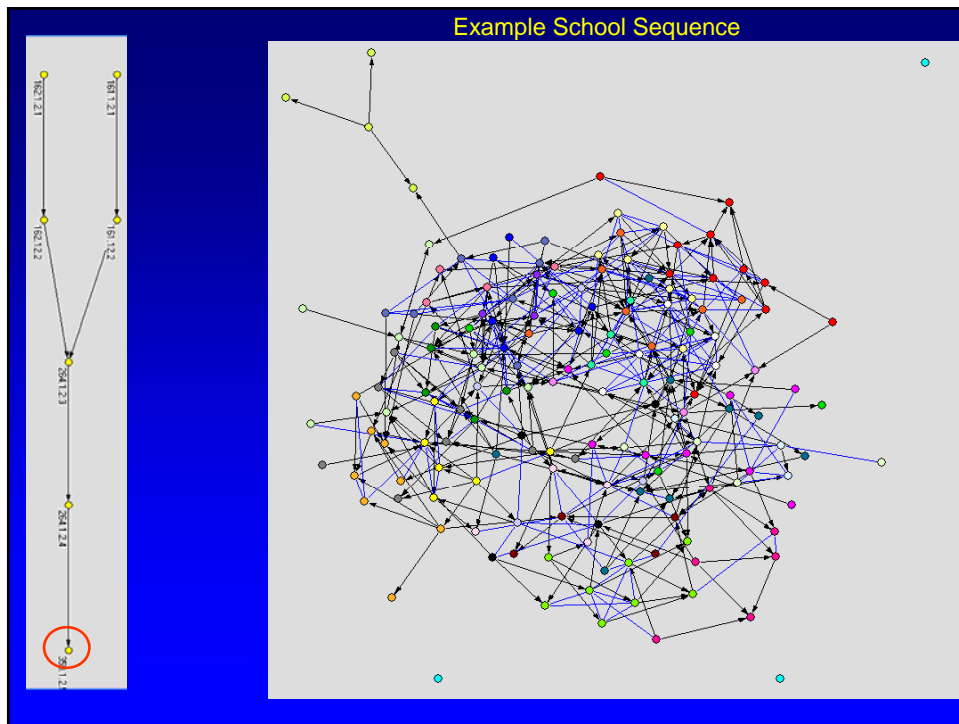


Example School Sequence

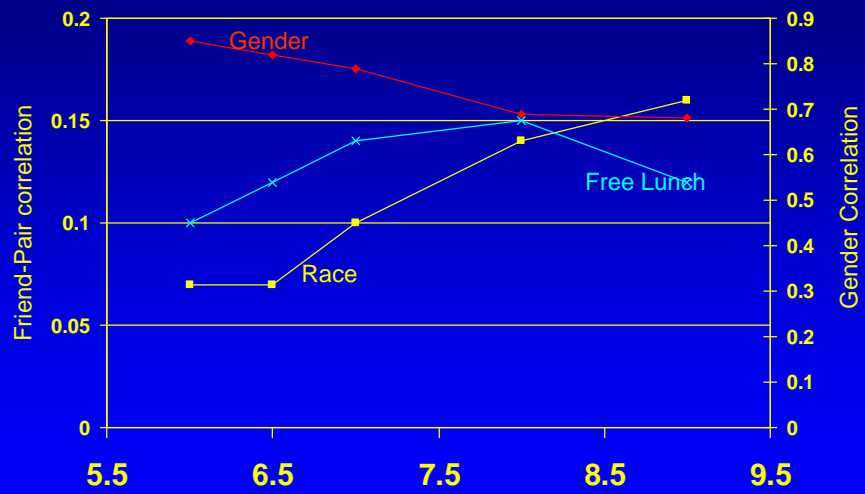


Example School Sequence

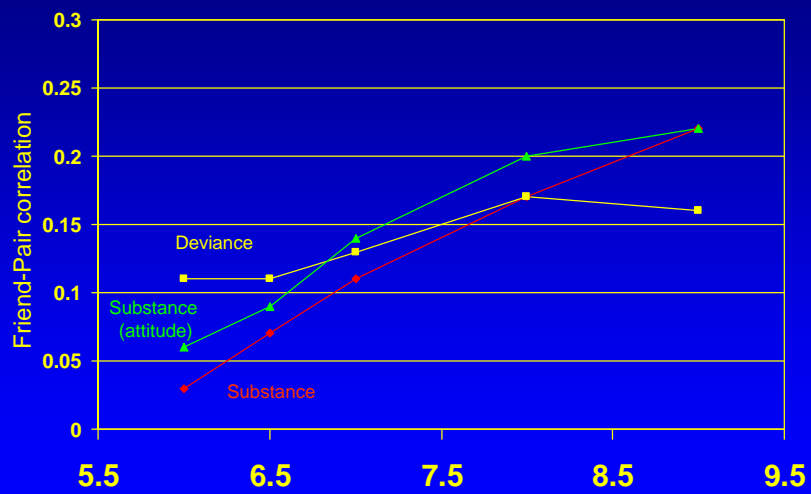




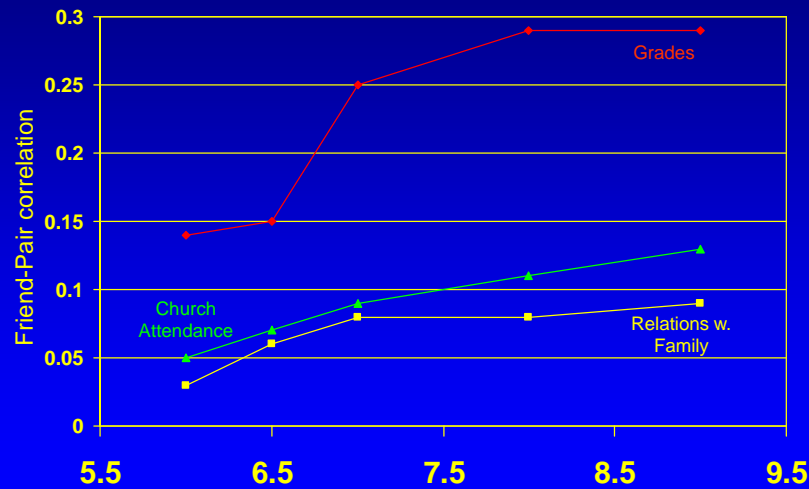
## Similarity for Demographics



## Similarity for Problem Behavior



## Similarity for Other Attributes



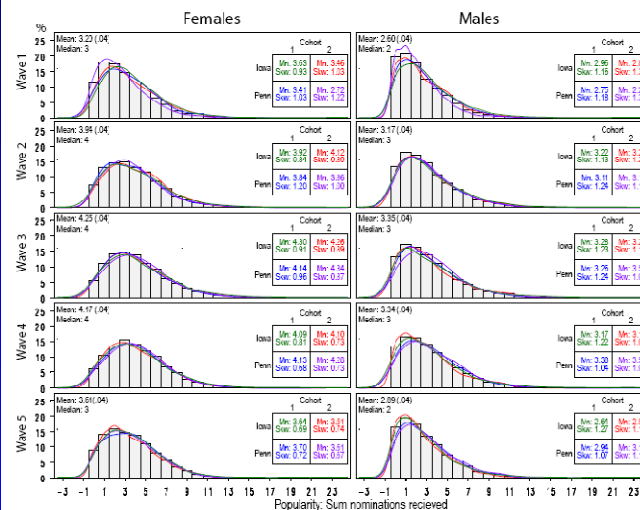
## Popularity Structure: Macro level stability

The shape of the popularity distribution is essentially constant over time and across each state/cohort combination.

Males differ from females in having greater numbers of people receiving zero nominations.

In all cases (and within each network), we get a fairly skewed distribution of popularity, reflecting a small number of very popular students.

Figure 1. Popularity Distributions  
By sex, wave, and setting

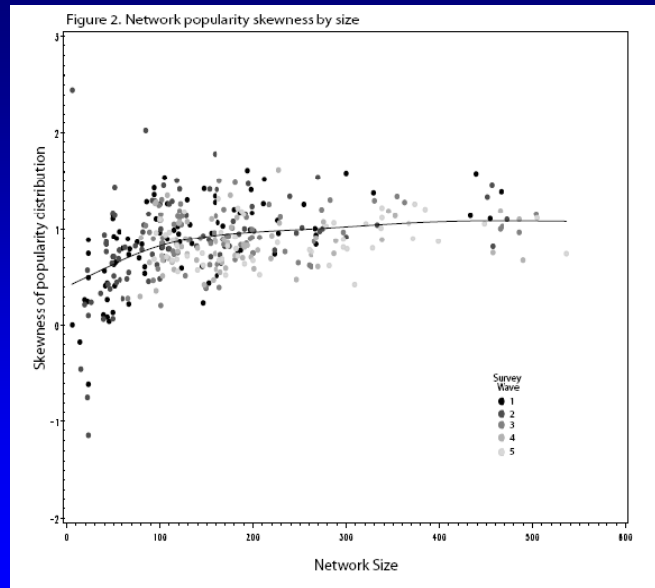


Bars pool observations within wave/sex combinations. Lines are kernel-smoothed histograms for each state-cohort combination; actual minimum observed scores are always 0. Colors match inset statistics and curves.



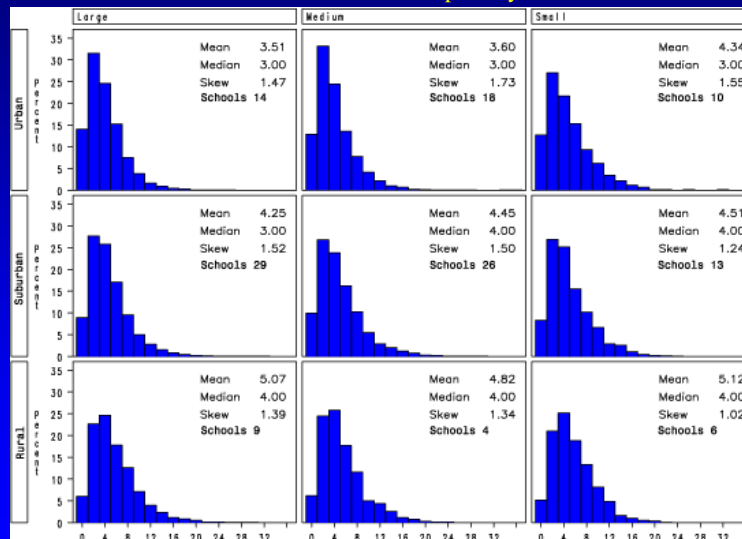
## Popularity Structure: Macro level stability

The Skewness coefficient captures the length of the tail of the popularity distribution, and is essentially constant across networks of more than ~100 students.



## Popularity Structure: Macro level stability Add Health comparison

### Distribution of Popularity

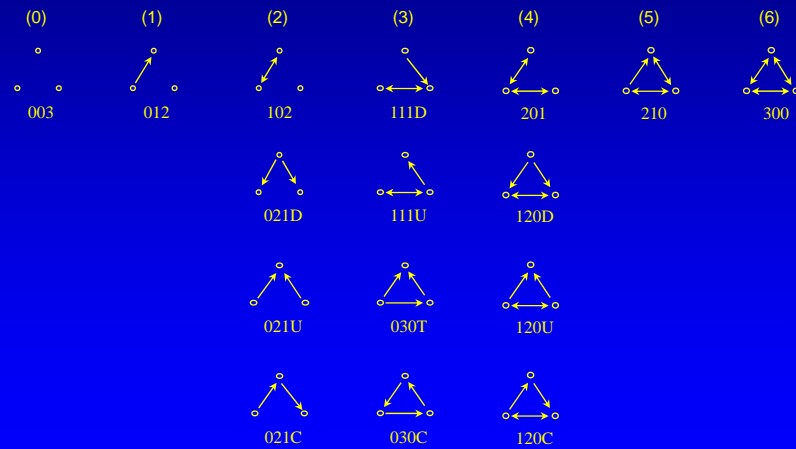


By size and city type

## Popularity Structure: Macro level stability

Linking Micro to Macro through Triad distributions

A periodic table of social elements:

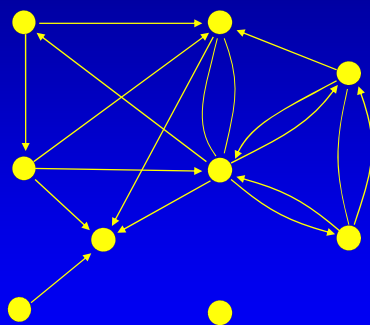


16 directed triads

## Popularity Structure: Macro level stability

Linking Micro to Macro through Triad distributions

A periodic table of social elements:

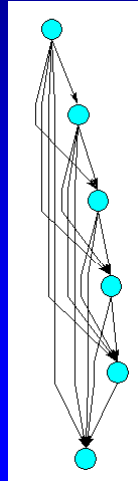


Type	Number of triads
1 - 003	21
2 - 012	26
3 - 102	11
4 - 021D	1
5 - 021U	5
6 - 021C	3
7 - 111D	2
8 - 111U	5
9 - 030T	3
10 - 030C	1
11 - 201	1
12 - 120D	1
13 - 120U	1
14 - 120C	1
15 - 210	1
16 - 300	1
Sum (2 - 16):	63

## Popularity Structure: Macro level stability

Linking Micro to Macro through Triad distributions

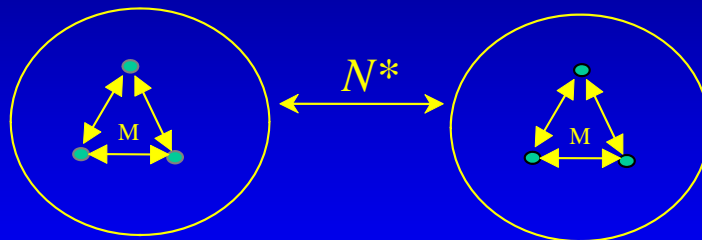
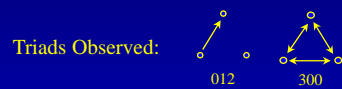
The distribution of triads found in any network limits its structure.  
For example, if all triads are 030T, then the network must have a perfect linear hierarchy.



(note this is what chickens do...)

## Popularity Structure: Macro level stability

Linking Micro to Macro through Triad distributions

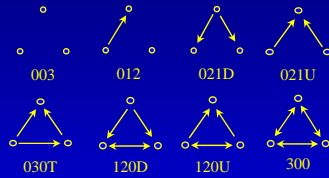


1	0
0	1

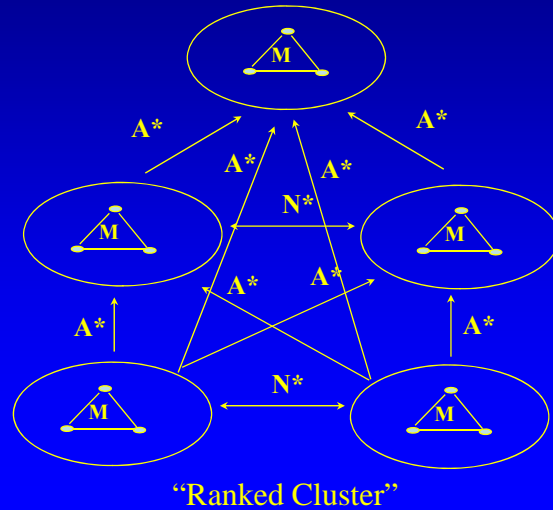
## Popularity Structure: Macro level stability

Linking Micro to Macro through Triad distributions

### Triads Observed:



Eugene Johnson (1985, 1986) specifies a number of structures that result from various triad configurations



## Popularity Structure: Macro level stability

Linking Micro to Macro through Triad distributions

The observed distribution of triads can be fit to the hypothesized structures using weighting vectors for each type of triad, using formulas for the conditional expectation of the triad counts.

$$\tau(l) = \frac{(l'T - l'\mu_T)}{\sqrt{l'\Sigma_T l}}$$

Where:

$l$  = 16 element weighting vector for the triad types

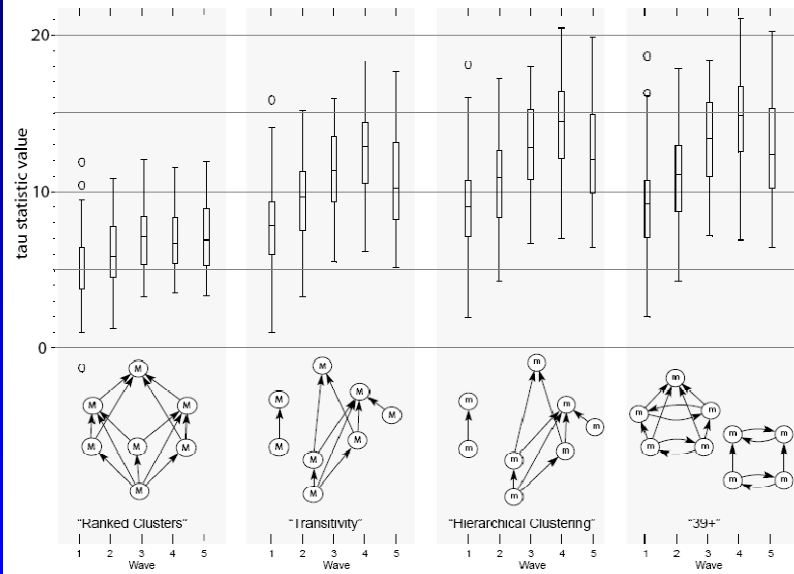
$T$  = the observed triad census

$\mu_T$  = the expected value of  $T$

$\Sigma_T$  = the variance-covariance matrix for  $T$

## Popularity Structure: Macro level stability

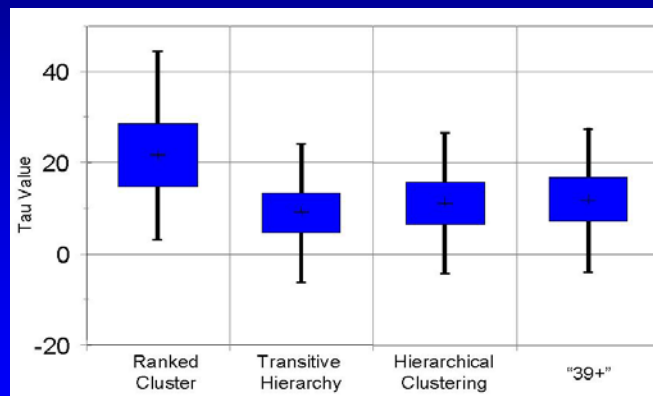
Figure 3. Triad macro-structure model results for PROSPER school networks.



## Popularity Structure: Macro level stability

### Add Health comparison

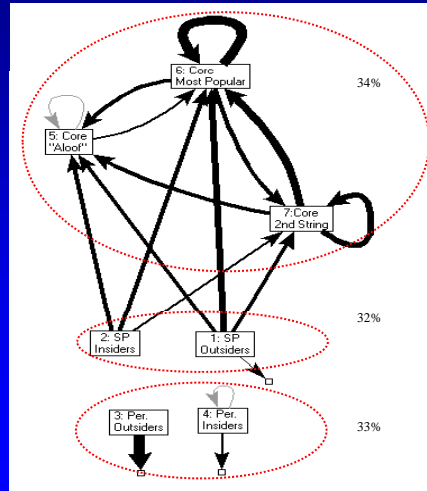
For the 129 Add Health school networks, the observed distribution of the  $\tau$  statistic for various models is:



Suggesting that the "ranked-cluster" models beat random chance in all schools.

Popularity Structure: Macro level stability  
Add Health comparison

Jefferson High School



Sunshine High School

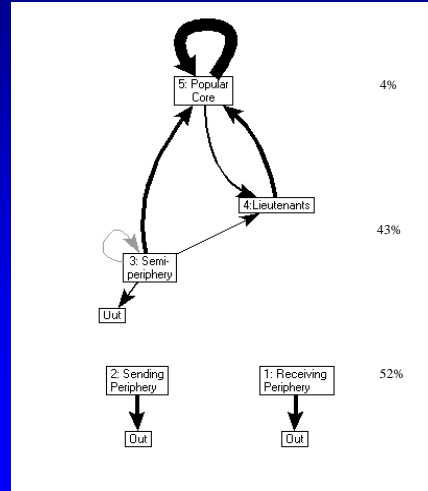
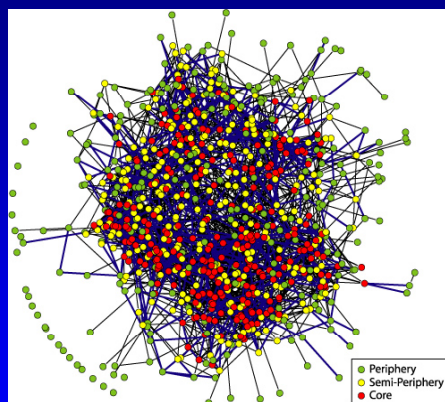


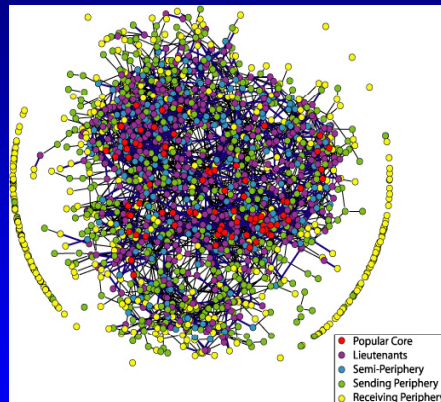
Image networks. Width of tie is proportional to the ratio of cell density to mean cell density.

Popularity Structure: Macro level stability  
Add Health comparison

Jefferson High School

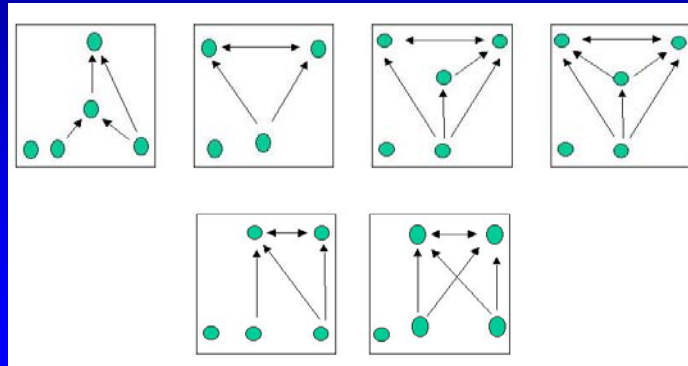


Sunshine High School



Popularity Structure: Macro level stability  
*Add Health comparison*

If we impose a 5-block solution on *all* 129 networks, we find a similar clear hierarchy in each school, differing only in the number of levels that might form a 'semi-periphery' position in the network.



Over half of the networks had one of these 6 image networks

Micro mobility within settings (Prosper again!)

While the structure appears constant, relations are fluid:

**Tables**

Table 1. Proportion of nominations matching across waves.

		Wave 2	Wave 3	Wave 4	Wave 5
Fall 6 <sup>th</sup> Grade	Wave 1	0.49	0.26	0.19	0.14
Spring 6 <sup>th</sup> Grade	Wave 2		0.29	0.20	0.14
Fall 7 <sup>th</sup> Grade	Wave 3			0.32	0.21
Fall 8 <sup>th</sup> Grade	Wave 4				0.29

Within a year (6<sup>th</sup> Fall to 6<sup>th</sup> spring), 49% of nominations remain, dropping to 14% across the 5 waves.

This suggests a very dynamic setting with lots of local network "churning"

## Micro mobility within settings (Add Health again!)

While the structure appears constant, relations are fluid:

Add Health relational change statistics

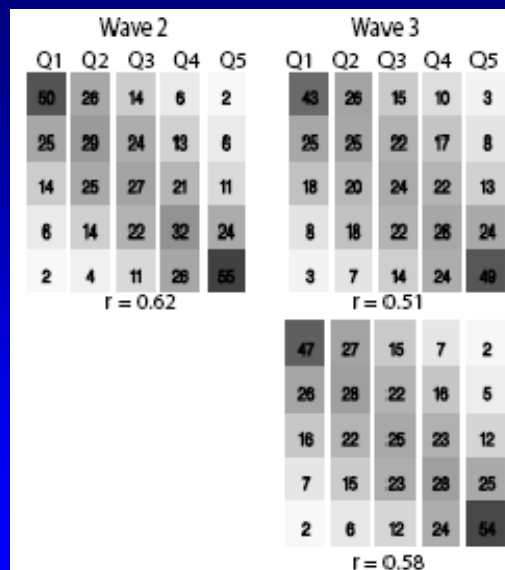
	Wave 1				Wave 2			
	Jefferson	Sunshine	Small Sats	All Schools	Jefferson	Sunshine	Small Sats	All Schools
In-School								
All Friends	51%	48%	62%	58%	40%	41%	52%	47%
Same Sex	58%	57%	69%	66%	48%	48%	60%	56%
Same Race	51%	51%	62%	59%	40%	43%	52%	48%
Same Grade	56%	53%	66%	62%	46%	47%	57%	52%
Reciprocated	77%	83%	83%	83%	77%	80%	80%	82%
Wave 1								
All Friends					45%	46%	37%	44%
Same Sex					55%	49%	40%	50%
Same Race					47%	49%	36%	45%
Same Grade					51%	50%	38%	47%
Reciprocated					78%	77%	65%	75%

Proportion of time2 friends who were also friends in time1

## Micro mobility within settings

Here we see (normalized) mobility tables, looking at movement between quintiles of the popularity distribution.

While most movement is short-distances, there is a good deal of movement in overall status. Only half of the most/least popular kids remain so a year later, dropping to between 30 and 40 across wider time-spans.



Tables on popularity quintiles, correlations on percentile-rank between each wave.

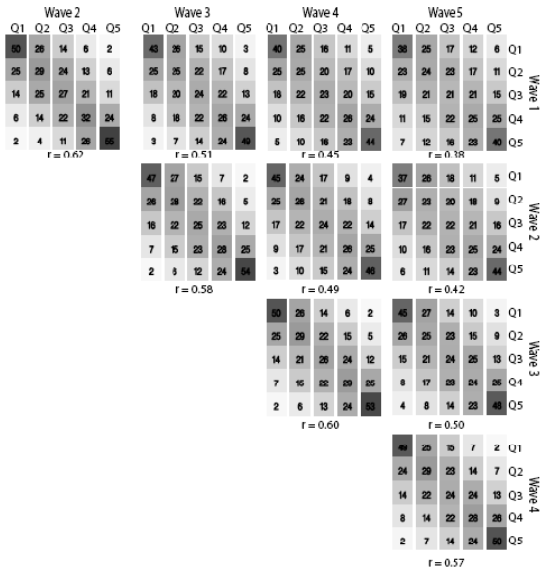


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Figure 4. Popularity Mobility Tables  
Marginal Normalized, by wave.



Tables on popularity quintiles, correlations on percentile-rank between each wave.

## Micro mobility within settings

Table 2: Popularity trajectory. Number of times a student spent in the bottom (row) and top (column) quintile.

Times in bottom quintile	Times in top quintile							
		0	1	2	3	4	5	Total
	0	16.3	13.2	10.0	7.8	5.9	3.9	57.1
	1	13.8	4.8	1.8	0.5	0.2		21.2
	2	9.1	1.2	0.2	0.0*			10.5
	3	5.7	0.3	0.0*				5.9
	4	3.3	0.0					3.4
	5	1.9						1.9
	Total	50.1	19.6	12.0	8.4	6.0	3.9	100

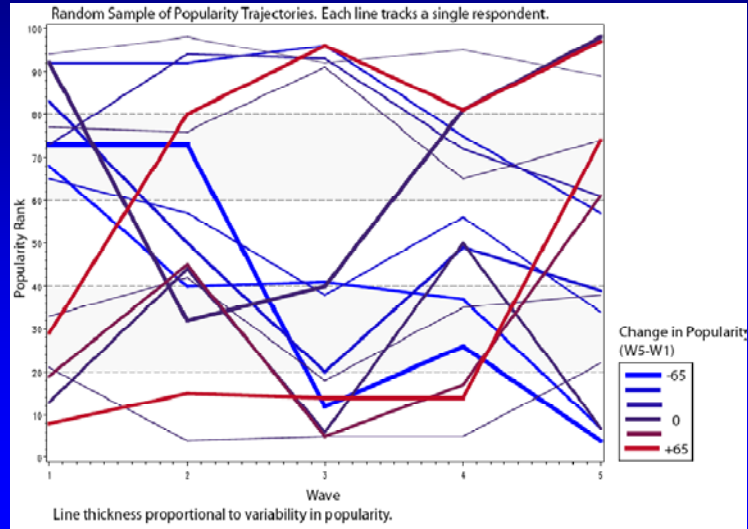
Since the sum of row/column cannot exceed 5 some cells are undefined, indicated by shading. \*=rounds to zero. N=8936

An individual-based perspective: chances of being in the top quintile x times given time in the bottom quintile.

For example only 3.9% of kids are in the most popular quintile all 5 waves, and a full 50% are in the top quintile at least once over the observation period. Similarly, only 1.9% of kids are least popular all 5 waves, but 43% are least popular at least once.

### Micro mobility within settings

Another view: Tracking trajectories over time. Here we have a random sample of 15 kids' trajectories, with increasing popularity in red, decreasing in blue. Note the many different patterns...



### Micro mobility within settings (Add Health)

An individual's position in the status hierarchy is also not stable:

Jefferson	Bottom 20%	2 <sup>nd</sup> quintile	3 <sup>rd</sup> quintile	4 <sup>th</sup> quintile	9 <sup>th</sup> decile	10 <sup>th</sup> decile
In-School:W1	$\chi^2=391, df=25, p<.001$					
Bottom 20%	46 (52%)	35 (39%)	4 (4.5%)	4 (4.5%)	0	0
2 <sup>nd</sup> quintile	49 (34%)	53 (37%)	17 (12%)	22 (15.5%)	1 (.7%)	0
3 <sup>rd</sup> quintile	17 (14%)	40 (33%)	21 (17.5%)	33 (27.5%)	7 (6%)	2 (4.7%)
4 <sup>th</sup> quintile	10 (6.7%)	25 (16.7%)	19 (12.7%)	65 (43.3%)	21 (14%)	10 (6.7%)
9 <sup>th</sup> decile	0	7 (11.3%)	6 (9.7%)	18 (29%)	16 (26%)	15 (24%)
10 <sup>th</sup> decile	0	0	2 (4%)	12 (23%)	12 (23%)	26 (50%)

Sunshine	Bottom 20%	2 <sup>nd</sup> quintile	3 <sup>rd</sup> quintile	4 <sup>th</sup> quintile	9 <sup>th</sup> decile	10 <sup>th</sup> decile
In-School:W1	$\chi^2=495, df=25, p<.001$					
Bottom 20%	87 (52%)	47 (28%)	18 (11%)	6 (4%)	7 (4%)	1 (1%)
2 <sup>nd</sup> quintile	74 (32%)	78 (33%)	39 (17%)	21 (9%)	16 (7%)	7 (3%)
3 <sup>rd</sup> quintile	77 (18%)	103 (24%)	92 (22%)	78 (18%)	60 (14%)	18 (4%)
4 <sup>th</sup> quintile	14 (13%)	26 (23%)	22 (20%)	19 (17%)	26 (23%)	5 (5%)
9 <sup>th</sup> decile	10 (6%)	18 (10%)	30 (17%)	37 (20%)	61 (34%)	26 (14%)
10 <sup>th</sup> decile	1 (1%)	5 (5%)	7 (7%)	11 (10%)	39 (36%)	45 (42%)

## Capturing Trajectories

### Tracking Trajectories:

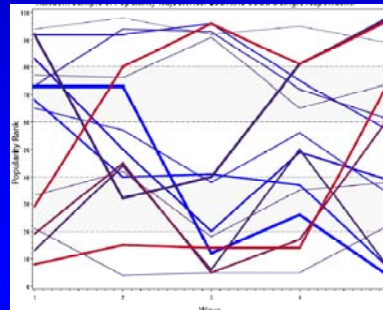
How do we characterize a popularity trajectory?

#### - Cluster analysis:

- Goal is to find similar patterns across the set of 5-wave trajectories.
- Advantage: you have great flexibility in the actual pattern
- Disadvantages:
  - Exploratory & can capitalize on randomness
  - Time/Data intensive
  - Need to decide on numbers-of-clusters

-In the end this was not convincing:  
no clear separation in the clusters nor interpretable clustering tree.

-Instead, what jumps out is the sheer variability in experiences across cases.



## Capturing Trajectories

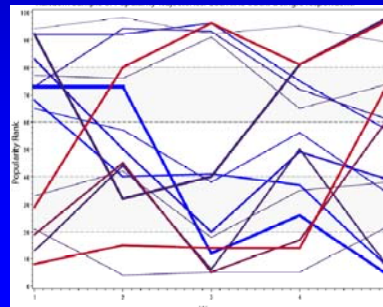
### Tracking Trajectories:

Smooth "field of experiences" approach:

- Fit a simple linear model to change over time *for each student*.: the combination of intercept and slope then describe the "general" trajectory of popularity each student experiences....

...but, the trend removes all the variability in movement around the trend; which is likely important for one's experience in the setting: we want to distinguish a steady trajectory from a wildly swinging one. So we add an additional indicator of the standard deviation of popularity to the model.

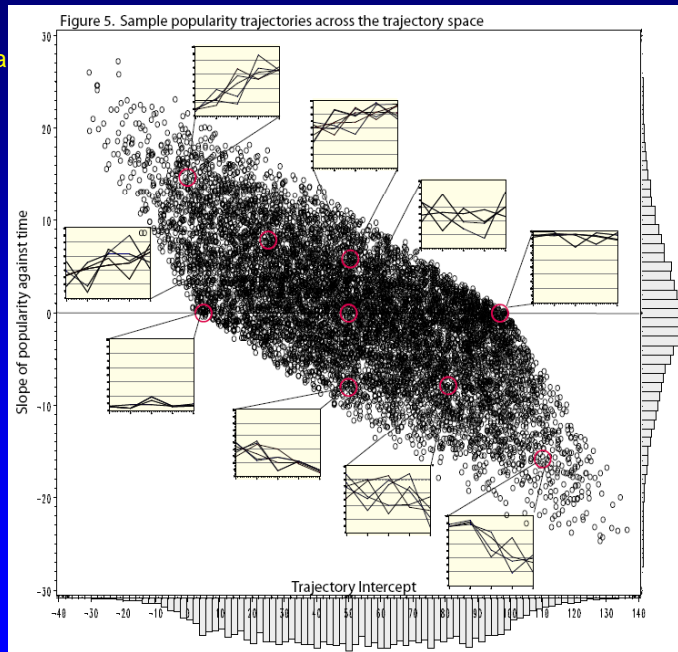
Combined, these two features (regression parameters & variance) capture the direction and "width" of trajectory experiences.



### Capturing Trajectories

The regression estimates define a simple 2-d space of slope (Y) and intercept (x).

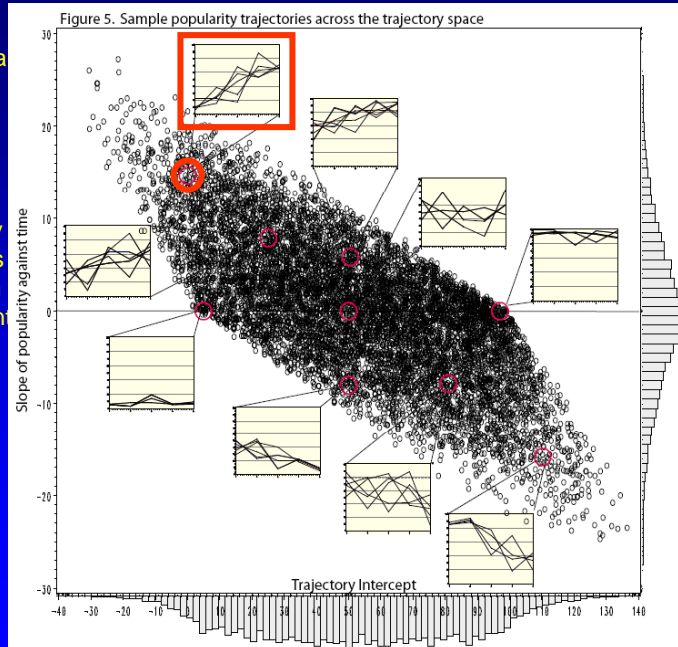
This figure represents the distribution of cases across that space, with key points labeled.



### Capturing Trajectories

The regression estimates define a simple 2-d space of slope (Y) and intercept (x).

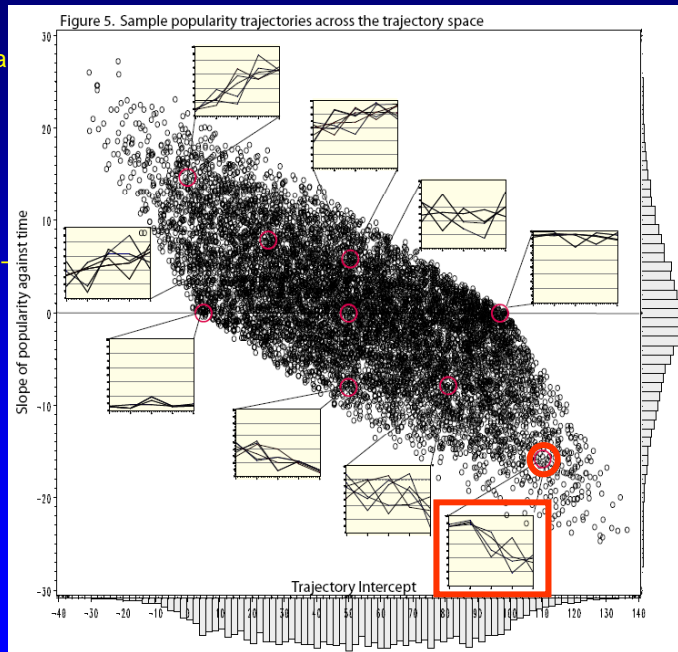
This region represents steady & sharp increases in popularity, from a low starting point to a high ending point. These kids are upwardly mobile



### Capturing Trajectories

The regression estimates define a simple 2-d space of slope (Y) and intercept (x).

In contrast, here we have steady but sharp decline – these kids are downwardly mobile.

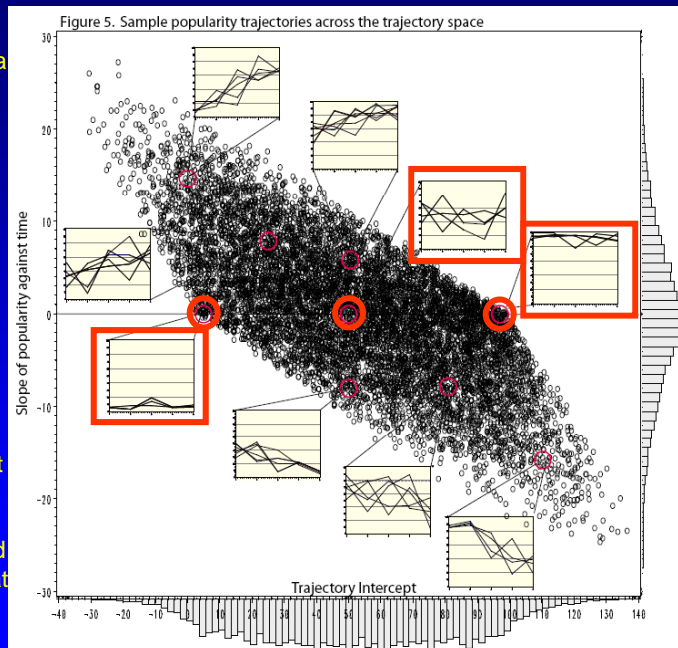


### Capturing Trajectories

The regression estimates define a simple 2-d space of slope (Y) and intercept (x).

...and three "steady" states: kids with stable popularity.

Note there is no clumping in the space, but a true continuous field, and also note that variability is correlated with slope, so we need to disentangle that in the models.



### Capturing Trajectories

There is thus a large variety in status trajectories over time, and this trajectory has two salient features:

- Direction: Increasing or decreasing at different rates
- Variability: Steady state or wide swings in trajectory over time

How this micro-view meshes with the stable macro-structure is beyond the scope of the current paper, but in general shifts in mobility must be coordinated across third parties to ensure that the triad-distributions remain largely consistent with a hierarchical order at each wave. This likely (!) rests on some variant of peer-balance models.

For now, we turn to the question of how popularity mobility affects substance use.

### Popularity Trajectory & Substance use (reminder)

Status in youth culture is often associated with activities that are (perceived as) more adult than most peers or in direct opposition to adult constraints/expectations. Thus:

**Main Effect:** we expect a positive association between substance use and popularity: in the cross-section, popular students should use substances (smoke, drink, drugs) more often than students who are less popular.

Trajectory Effects:

- To the degree that substance use confers status, *those gaining status* should start using at a higher rate. This is a "snowballing" effect of status, where the newly-ranked used more to shore up their status among peers.
- However, *loss of status* should lead to desperation and an attempt on the actors part to re-capture status, also leading to an increase in use, to a higher degree than (a).
- Similarly, high variability in status should create uncertainty that also leads to greater use.

## Popularity Trajectory & Substance use

Substance use is an Item-Response-Theory construction of reported use with respect to Smoking, Drinking and Marijuana use in the month preceding the interview.

Cross-sectional models show a consistent positive effect of popularity on substance use, matching prior work.

For trajectories, we use a network-level random effects model (random intercepts for each network setting) that conditions on prior use. Here we are modeling use in waves 4 and 5 as a function of trajectory slope/intercept.

We test two trajectory models; a simple “mean popularity” model to replicate the cross-section effects and a model that replaces mean use with the regression slope & intercept and the standard deviation of popularity over time.

## Popularity Trajectory & Substance use

Table 4. Trajectory models with setting-level random intercepts. Standard errors in parentheses.

	Model 1	Model 2	Model 3	Model 4
Intercept	0.286 *** (0.041)	0.175 *** (0.031)	0.303 *** (0.04)	0.178 *** (0.035)
Mean Popularity (div by 10)	0.034 *** (0.003)	0.022 *** (0.003)		
Standard Deviation of Popularity	0.005 *** (0.001)	0.003 *** (0.001)	0.005 *** (0.001)	0.002 *** (0.000)
Popularity Trend Slope			0.003 *** (0.001)	0.004 *** (0.001)
Popularity Trend Intercept			0.003 *** (0.000)	0.002 *** (0.000)
Lagged Substance Use Score		0.640 *** (0.008)		0.639 *** (0.009)
Wave 5	0.234 *** (0.023)	0.126 *** (0.017)	0.243 *** (0.023)	0.130 *** (0.018)
Male	-0.013 (0.014)	-0.016 (0.012)	-0.042 ** (0.015)	-0.040 ** (0.013)
White	-0.100 *** (0.018)	-0.048 ** (0.016)	-0.101 *** (0.020)	-0.047 ** (0.018)
Cohort 1	0.011 *** (0.029)	0.053 *** (0.020)	0.114 *** (0.029)	0.055 ** (0.021)
Iowa	-0.086 ** (0.029)	-0.029 (0.020)	-0.074 *** (0.029)	-0.026 (0.021)
Level 1 N : 109				
Level 2 N: 17,393				
-2 Log L	52,335	40980	41264	33090

\* p < 0.05; \*\* ≤ 0.01, \*\*\* ≤ 0.001

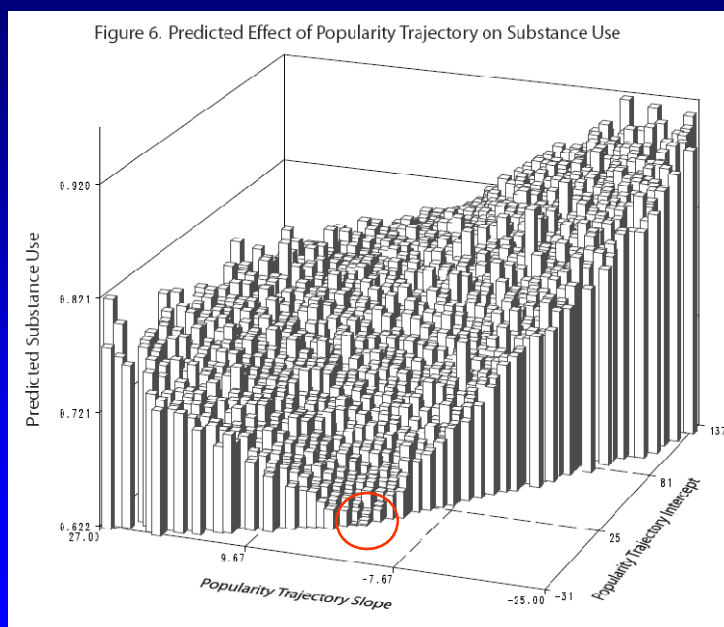


## Popularity Trajectory & Substance use

Predicted substance use from final model:

This surface reflects the predicted effect of popularity trajectory, the x-y axis are the slope and intercept of trajectory

The circled area would be a person with consistently low popularity.

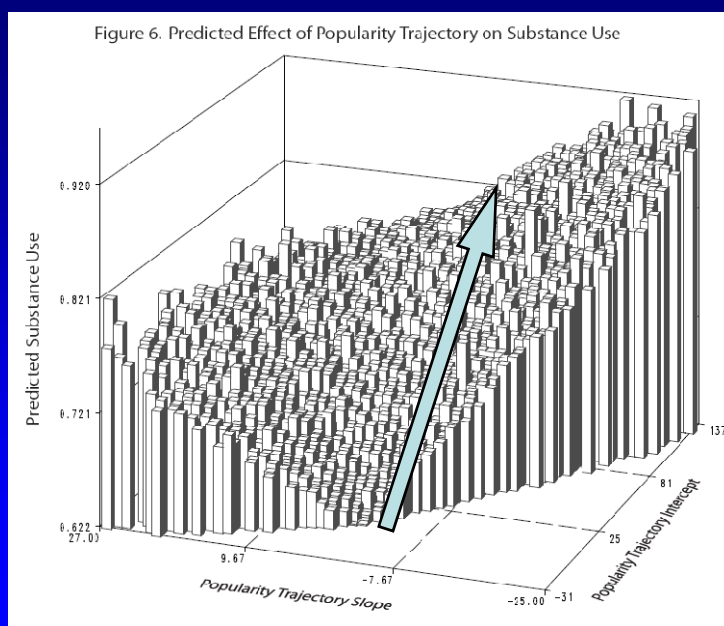


## Popularity Trajectory & Substance use

Predicted substance use from final model:

At slope=0, we see the main effect of popularity as increasing along the X axis:

There is a strong and steady increase in use as popularity goes up.

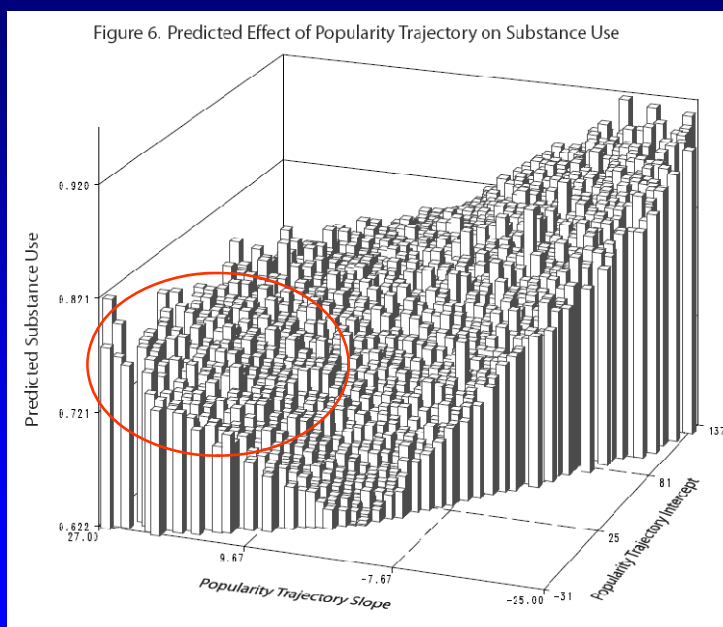




## Popularity Trajectory & Substance use

Predicted substance use from final model:

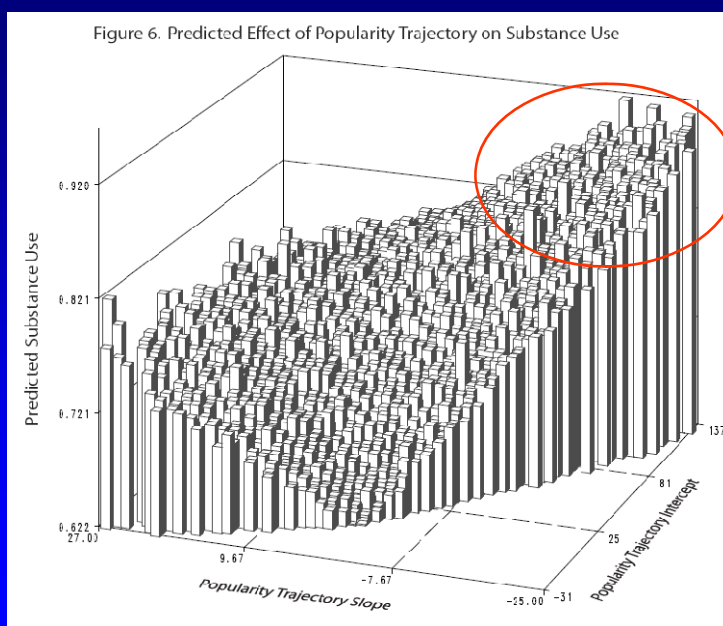
When slope is positive, kids are becoming more popular, and we see an increase in use...



## Popularity Trajectory & Substance use

Predicted substance use from final model:

But even stronger use among those with decreasing substance use.



## Conclusion

These new data allow us to match changes in network position to behavior over time and across settings. Here we find:

- Strong evidence of social hierarchy across settings (that is somewhat stronger in later waves).
- Much mobility within the structure as local friends are unstable and position within the hierarchy changes over time
- A consistent positive relation between popularity and substance use.

This represents a first-look at these new data, and there are many more directions to pursue. In particular, we want to explore:

- Popular with who?
- By category (Male or female) and position (popular or unpopular)
- Relative effect of peer influence and network position.