Peer or Spillover Effects:

Modeling the Effect of Social Dynamics on Actors' Outcomes

Manuel S. González Canché
Associate Professor
✉: **msgc@upenn.edu** : **@manu_canche**

Higher Education & Quant. Methods Division

Graduate School of Education Penn GSE

November 1, 2022

Background...

QR text: https://cutt.ly/bNUBYvm

Figure 1: Access to full study

One Page Summary

- We assume that after **random assignment** and participants' **take-up**, a comparison of **treatment and control** participants' baseline characteristics is a valid indication of them being **similar**
  - The study shows how one can employ network analysis principles and geostatistics to **comprehensively test** the validity of this **standard assumption**
- Another assumption is **SUTVA**, no interference, one version of the treatment or **no spillover effects**
  - The study shows this is another **troubling assumption**.
- In sum, baselines **may be compromised** and **spillover effects** do exist, both of which are important threats to the **validity of causal claims**.

Evolution & Set Up of the Presentation

- The quantitative training I received led me to measure **outcome dependence** relying on **spatial econometric** techniques
  - Main motivation was to reach **less biased inferences** by addressing violations of model residuals not being *i.i.d.*
- As time passed this interest has fortunately **evolved**
  - These same techniques that deal with outcome dependence allow to powerfully test for **spillover or peer effects** (way cooler!).
- This is **not going to be a highly technical presentation**, the math works, rather I will focus on the **"so what" or implications and major takeaways**.

I. Why to Focus on Outcome Dependence?

- "Everything is related to everything else, but near things are more related than distant things" (Tobler, 1970, p. 236), AKA as the first law of geography, captures the notion of **spatial dependence or autocorrelation**.
- This law uses distances to establish connections and these connections enable the testing of **local competition and/or dependence**.
- There are remarkable points to note
  1. Spatial **independence** remains the least tested property in most social sciences
  2. The **spatial econometric framework** has a 1 to 1 transferability to the **statistical network analysis framework**,
  3. This **law** can be **extrapolated** to connections measured using social measures. . .

II. Why to Focus on Outcome Dependence?

- Scholars **love** using the term **networks, peer effects, spillover effects.**
- However, **formal methods** used to assess hypotheses about these terms remain fairly **unused**.
- Instead, we typically **assume unit independence** or rely on **multi-level** and/or **clustered** models to capture students being **nested** in classrooms, for example.
  - While these models may **handle dependence**, they are still rarely used to test for **peer effects.**
- Today's discussion will focus on the rationale used to merge **network and spatial dependence** methods to measure **spillover** effects through **peer** effects using **socially** captured dependence.

Again. . . Why to Focus on Outcome Dependence?

Can you imagine a situation wherein this condition holds true?

Students' performances do not influence their peers' performances and are not simultaneously affected by them in return.

- Would this hold true for **Randomized Control Trials**?
- Maybe in **quasi-experiments**?
- Maybe in **personality tests**?
- . . .
- Most likely situation is that **performance is not merely individual**, rather is affected by **environmental and contextual** conditions and influenced by **peers**.

Again. . . Why to Focus on Outcome Dependence?

Can you imagine a situation wherein this condition holds true?

Students' performances do not influence their peers' performances and are not simultaneously affected by them in return.

- Would this hold true for **Randomized Control Trials**?
- Maybe in **quasi-experiments**?
- Maybe in **personality tests**?
- . . .
- Most likely situation is that **performance is not merely individual**, rather is affected by **environmental and contextual** conditions and influenced by **peers**.

Methodological Context

- **Correlation** is a unit free measure ...that can be seen from different perspectives:
  - **Statistics**: a measure of the extent to which two random variables (X and Y) vary together (covary) relative to the degree to which X and Y vary independently $\rho_{xy} = \left(\frac{\sigma_{xy}}{\sigma_x \sigma_y}\right)$
  - **Temporal data**: **serial autocorrelation** values measured close together in **time** are more similar than values measured far apart in time. Y_t at a previous times Y_{t-j}
  - **Spatial data**: **spatial autocorrelation** values measured **nearby in space** are more similar than values measured **farther** away from each other. Y_i at different distances $Y_{\Delta j}$
    - In the case of **social data**, same principles apply but we are still in the process of adapting these readily available methods.
    - Social sciences have paid close attention to **serial** autocorrelation, but almost none to **spatial and social** autocorrelation (big window of opportunity).

Network Thinking: Relational Data...

- A **network** consists of a group of **units** where a set of **connections** or links may be observed **(defined)**.
- When dealing with **spatial** data, connections are based on **physical distance**.
- When dealing with **social** data, connections are based on **our defining rules**. Let's talk about spatial cases first...

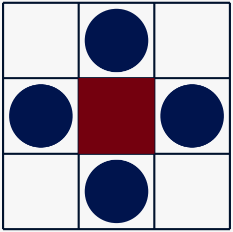


Figure 2: Rook's

Figure 3: Bishop's

Figure 4: Queen's

Network Thinking: Relational Data...

- A **network** consists of a group of **units** where a set of **connections** or links may be observed **(defined)**.
- When dealing with **spatial** data, connections are based on **physical distance**.
- When dealing with **social** data, connections are based on **our defining rules**. Let's talk about spatial cases first...

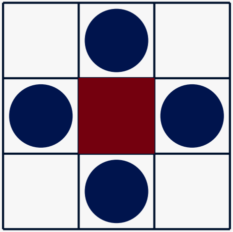


Figure 2: Rook's

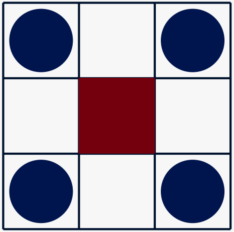


Figure 3: Bishop's

Figure 4: Queen's

Network Thinking: Relational Data...

- A **network** consists of a group of **units** where a set of **connections** or links may be observed **(defined)**.
- When dealing with **spatial** data, connections are based on **physical distance**.
- When dealing with **social** data, connections are based on **our defining rules**. Let's talk about spatial cases first...

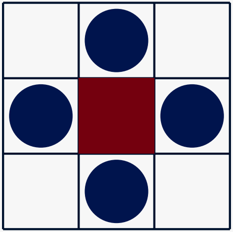


Figure 2: Rook's

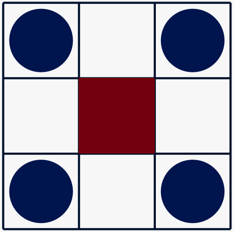


Figure 3: Bishop's

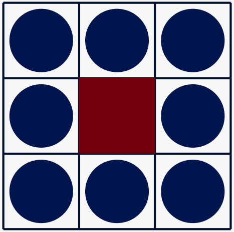


Figure 4: Queen's

Neighboring Structure Using Polygons

State−level Neighboring Structure

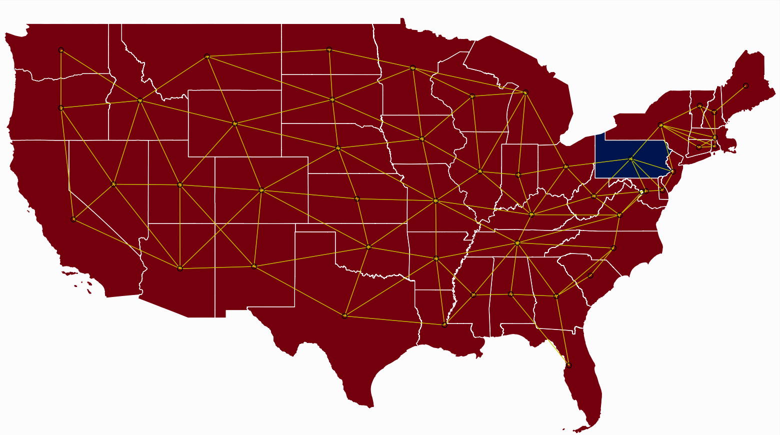


Figure 5: Neighbors at the state level

Neighbors Using Points

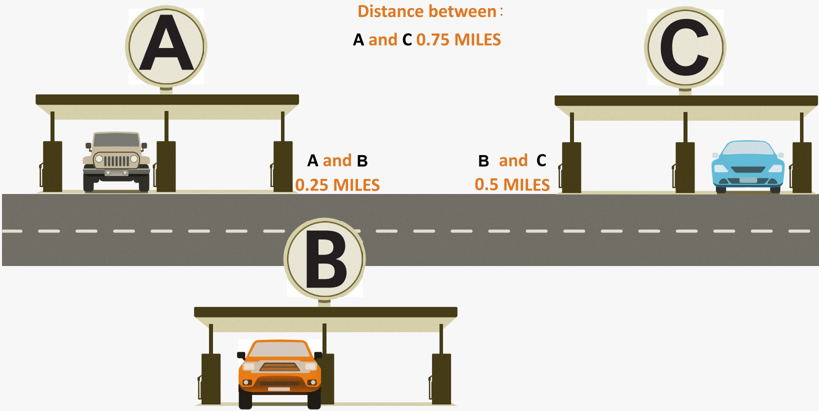


Figure 6: **Decision rule,** a neighbor will be the closest in terms of latitude and longitude coordinates. Identify the corresponding 1-k (or closest) neighbor specifications.

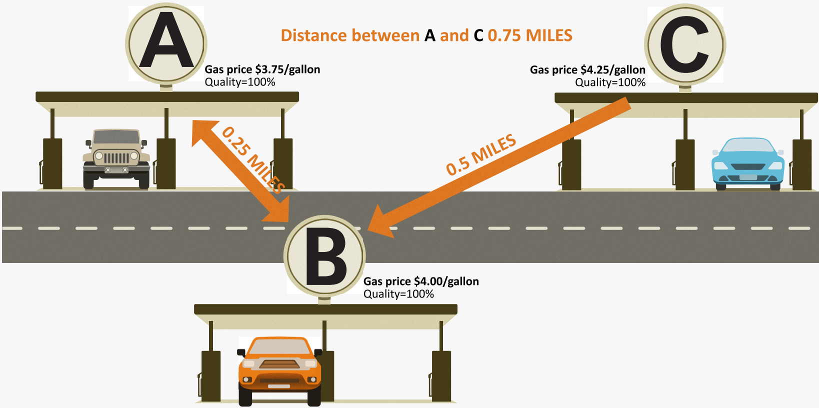


Figure 7: Local competition of gas prices (see Pinkse, Slade & Brett, 2000). This figure represents a 1-k specification from the spatial econometrics perspective.

Network of Neighboring Institutions

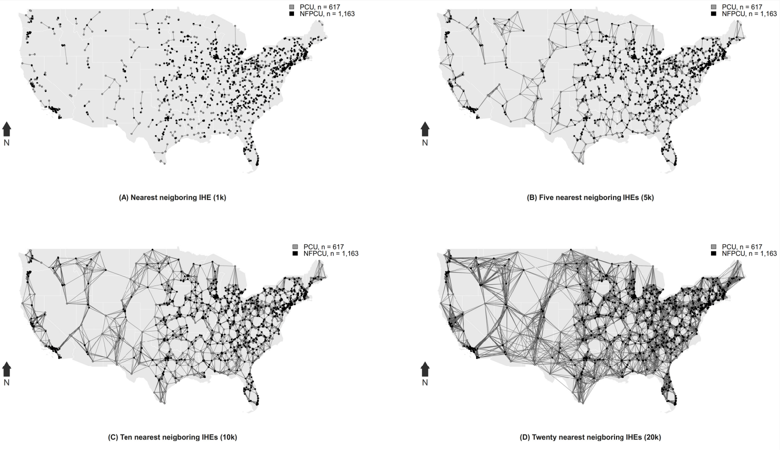
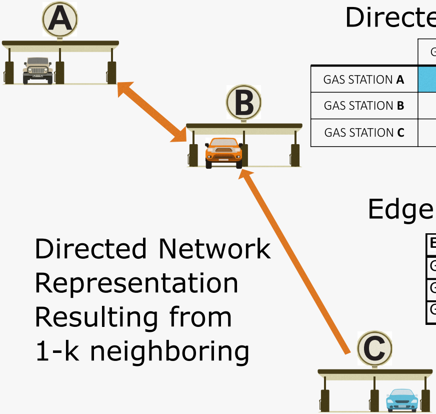


Figure 8: 1k, 5k, 10k, and 20k Neighboring Specifications

Network Analysis Framework: Relational Thinking



Directed Matrix of Influence

	GAS STATION **A**	GAS STATION **B**	GAS STATION **C**
GAS STATION **A**	–	**1**	**0**
GAS STATION **B**	**1**	–	**0**
GAS STATION **C**	**0**	**1**	–

Edgelist Representation

Ego	**Alter**
GAS STATION **A**	GAS STATION **B**
GAS STATION **B**	GAS STATION **A**
GAS STATION **C**	GAS STATION **B**

Figure 9: This figure represents a directed matrix specification and its corresponding edgelist from the network analysis perspective. **Powerful equation**:
edgelist$\leftrightarrow$network$\leftrightarrow$matrix$\rightarrow$Outcome dependence analyses

Complex Systems Application to Social Research

- **Complex systems** are configured by a **myriad of interactive elements** that likely **impact individual units'** outcomes, hence
  - not only is the analysis of **individual performance limited** in explaining the phenomenon under study
  - but also we can gain **better insights** by conceptualizing phenomena as **interconnected entities**.
- Complex systems can be used in **social and education** research in many contexts because...
  - **Dependence** takes place when outcomes or characteristics among **interconnected units** vary together
  - Once we can define **relational structures** we can model **dependence of any type**
  - Since **spatial econometric framework** has a 1 to 1 transferability to the **statistical network analysis framework**, we can **move beyond measures of distance** to apply analyses that model lack of independence issues.

Disclosure

The study

1. Was supported by a grant from the Institute of Education Sciences (R305A100670)
2. The content of the study does not represent the views of IES or my Co-PI (Dr. Pedro Portes, UGA).
3. All errors and/or misconceptions remain mine

Title

Complex Systems Network Approach to:
Assess Group-level Baseline Outcome Dependence
and Spillover Effects in Clustered Randomized Control Trials

Main Arguments . . .

- **Fundamental conditions** to reach **causality** in Randomized Control Trials (WWC, 2018)
  - Well-executed **random** assignment
  - **Participants' compliance** (take-up) of their assigned groups
  - **Baseline equivalence** tests that corroborate participants **look the same** in both observable and unobservable characteristics
  - **No spillovers** (no interference)

  - ~~**Fidelity of implementation,**~~
  - ~~**Total and differential attrition issues within acceptable margins**~~
  - ~~**Enough statistical power.**~~
- Study's main assertion: **Violations of random assignment, baseline equivalence, and spillovers** are **more prevalent** than captured by current approaches.

Basically, I ask, how realistic is to assume:

- That **group formation** and **pre-intervention performance** can be measured with **aggregated** baseline tests (treatment versus control group means), and
- That **peer interactions** have **no effect** on outcomes *i.e.*, my peer's have no effect on my performance and vice versa? (e.g., no spillover or contamination, interference effects).
- Accordingly, the study relies on **complex systems networks** to comprehensively
  - **assess baseline equivalences** of participants' pre-treatment assignment outcomes considering their **group-level pre-intervention** performance
  - **test for spillover effects**, or the influence of **participants' baseline** performances on their **peers' post-intervention** outcomes.

Research Questions...

- Is there **evidence of baseline outcome dependence** given students' **assignment to teachers**, regardless of treatment and control status?
  - If so, are these dependence issues **more pronounced among treated students** compared to dependence issues observed among their control counterparts?
- Is there **evidence of spillover effects** wherein students' performances are affected by the performance of their peers assigned to a given teacher?
  - If so, **are these effects moderated by treatment condition**? If yes, who benefits the most by the peers' performance, treated or control participants?
  - Do these spillover effects **disappear** when controlling for students' **own pre-treatment** performance?

Intervention: “The Instructional Conversation” (IC)

- IC is a **constructivist pedagogical approach** that seeks to make learning **meaningful and challenging** to students through the mastering of grade-level content based on teacher guided small group discussions
- In IC, teachers promote learning by **utilizing knowledge** of their students’ lived experiences to increase **student engagement** and motivation and the mastering of a high-quality curriculum
- IC takes place in **small groups** configured by **three to seven** students
- IC sessions **last about 20 minutes** and have a clear instructional goal, which can involve any subject matter.
- Students **regulate their own speaking turns**, and everyone is expected to contribute to the discussion and mastering of the content.

The current study...

- Does not seek to **assess the effectiveness** of the IC in improving student outcomes for that is covered in

  Portes, P. R., González Canché, M. S., Boada, D., & Whatley, M. E. (2018). Early Evaluation Findings from the Instructional Conversation Study: Culturally Responsive Teaching Outcomes for Diverse Learners in Elementary School. *American Educational Research Journal*, 55(3), 488-531.

- Here, instead I use that data to test the **usefulness of complex systems networks** in addressing the research questions posed.
- Data
  - **Seven** school districts, **20** schools, **29** teachers (19 IC), with 226 IC & 171 control fifth graders (**397** in total).
  - Variables: Standardized **fourth- (pre)** and **fifth**-grade (**post**) scores in math, reading, science, and English language arts.

- **Network Analyses**: Two-mode networks, students connected through their common exposure to teachers
  - Retrieve a row-standardized **one-mode network** $A * A^T = [(n,m) * (m,n)] = (n,n) = \frac{w_{ij}}{rowsums(w_{ij})}$
- Moran's I

$$I = \frac{n}{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}} \frac{\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\sum_{i=1}^{n}(y_i - \bar{y})^2}, \qquad (1)$$

	Individual	y_i	y_i-mean	y_j	y_j-mean	Cross-products	
T	A	85	**4.83**	89.50	**9.33**	45.11	**Consistently above** the mean, high values clustered with other high values
	B	92	**11.83**	86.00	**5.83**	69.03	
	C	87	**6.83**	88.50	**8.33**	56.94	
C	D	68	**-12.17**	74.50	**-5.67**	68.94	**Consistently below** the mean, low values clustered with other low values
	E	74	**-6.17**	71.50	**-8.67**	53.44	
	F	75	**-5.17**	71.00	**-9.17**	47.36	
Overall mean		**80.17**					

- **Multilevel Modeling**

$$Y_{it} = \beta_{0t} + \beta 1 t X_{1it} + \varepsilon_{it}, \text{ where } \beta_{0t} = \gamma_{00} + \eta 0t \quad (2)$$

  Accordingly, ε_{it} should behave **i.i.d.** after accounting for η_{0t}

- Alternatively, we can also rely on **Simultaneous Autorregressive (SAR) Modeling**

$$y_i = \lambda \sum_{j=1}^{n} w_{ij} y_j + X_i \beta + \boldsymbol{\varepsilon_i}, \quad (3)$$

- The **residuals** ε_i are modeled as follows

$$e_i = \sum_{i=1}^{m} w_{ij} e_i + \varepsilon_i, \quad (4)$$

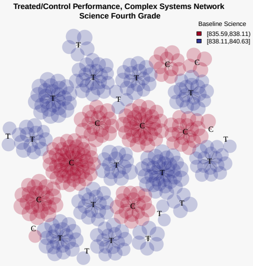
- We can then use **Moran's I** to test whether these residuals (ε_{it} and ε_i) **are free** of units' connections' influence

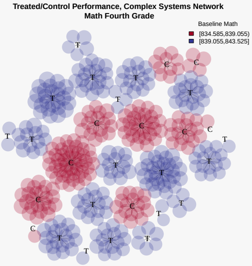
Findings

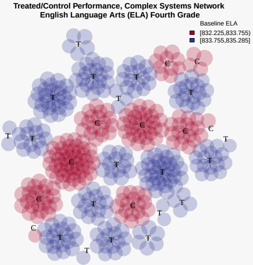
Table 1.

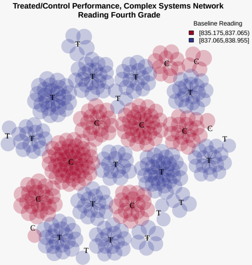
Baseline Indicators by Treatment and Control Condition

Variable	Levels	n	Mean	S.D.	Min	Max
pre_science	Control	171	836.8	40.3	750	956
	Treatment	226	839.4	42.8	740	956
p= 0.55	Total	397	838.3	41.7	740	956
pre_math	Control	171	836.8	36.2	762	940
	Treatment	226	841.3	45.7	735	990
p= 0.29	Total	397	839.4	41.9	735	990
pre_ela	Control	171	833	28.3	768	930
	Treatment	226	834.5	30	758	930
p= 0.61	Total	397	833.9	29.3	758	930
pre_read	Control	171	836.1	27.5	774	912
	Treatment	226	838	30.2	762.5	912
p= 0.52	Total	397	837.2	29.1	762.5	912









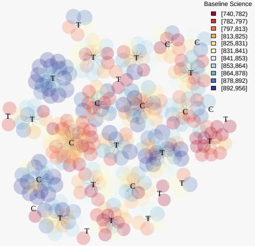
*Naïve approach

Table 2.

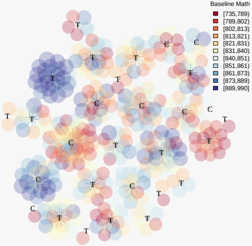
Complex Systems Network Analysis of Baseline Performance Given Teacher Assingment

Groups	**Variable**	**Moran's I**	**Expectation**	**Standard Deviate**	**Prob.**
Treatment and control	pre_science	0.34359	-0.0026	17.952	< 0.001
	pre_math	0.39136	-0.0026	20.464	< 0.001
	pre_ela	0.32441	-0.0026	16.977	< 0.001
	pre_read	0.37125	-0.0026	19.388	< 0.001
Treatment	pre_science	0.38923	-0.0045	13.949	< 0.001
	pre_math	0.43896	-0.0045	15.756	< 0.001
	pre_ela	0.38421	-0.0045	13.794	< 0.001
	pre_read	0.3919	-0.0045	14.044	< 0.001
Control	pre_science	0.27327	-0.006	12	< 0.001
	pre_math	0.28536	-0.006	12.534	< 0.001
	pre_ela	0.23734	-0.006	10.354	< 0.001
	pre_read	0.27627	-0.006	12.136	< 0.001
Under True Random assignment at the teacher level					
Treatment and control	pre_science	-0.0294	-0.0025	-1.3624	0.9135
	pre_math	-0.0185	-0.0025	-0.81	0.791
	pre_ela	-0.0099	-0.0025	-0.3747	0.646
	pre_read	0.00026	-0.0025	0.14123	0.4438

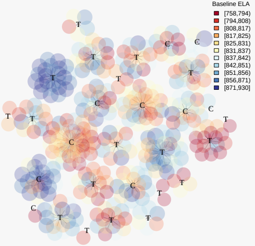
Individual Performance, Complex Systems Network
Science Fourth Grade



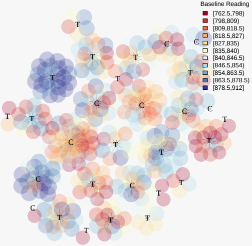
Individual Performance, Complex Systems Network
Math Fourth Grade



Individual Performance, Complex Systems Network
English Language Arts (ELA) Fourth Grade

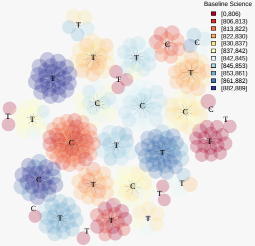


Individual Performance, Complex Systems Network
Reading Fourth Grade

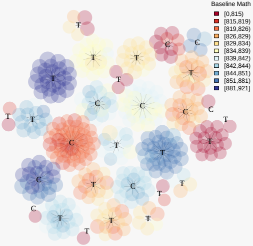


*Individual-based Outcome approach

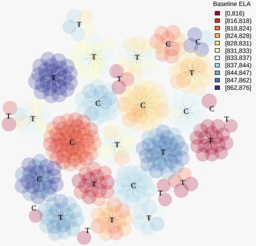
Group Performance, Complex Systems Network
Science Fourth Grade



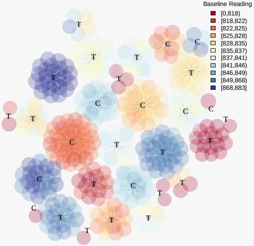
Group Performance, Complex Systems Network
Math Fourth Grade



Group Performance, Complex Systems Network
English Language Arts (ELA) Fourth Grade

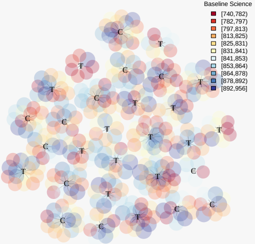


Group Performance, Complex Systems Network
Reading Fourth Grade

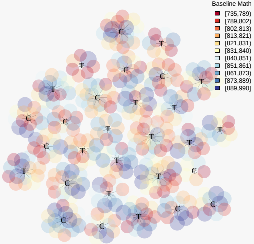


*Group-based outcome approach

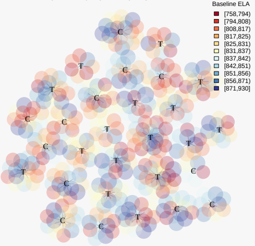
Individual Performance, Complex Systems Network
Science Fourth Grade



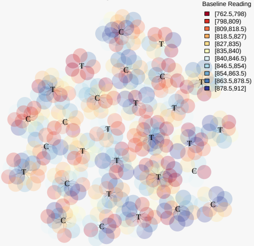
Individual Performance, Complex Systems Network
Math Fourth Grade



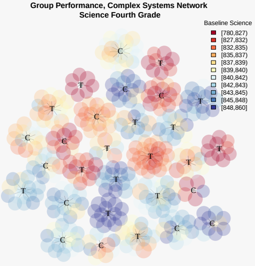
Individual Performance, Complex Systems Network
English Language Arts (ELA) Fourth Grade

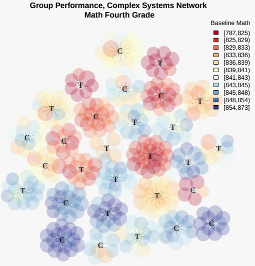


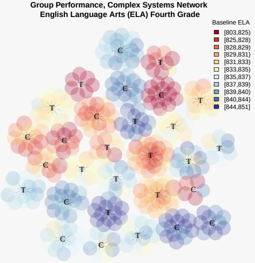
Individual Performance, Complex Systems Network
Reading Fourth Grade

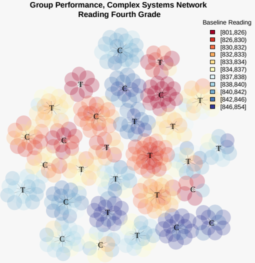


*Truly random individual-based outcome approach









*Truly random group-based outcome approach

Table 3.

Regression Models Explaining Post-Intervention Outcomes Using Spillover Effects

	OLS				Multilevel			
	Science	**Math**	**ELA**	**Reading**	**Science**	**Math**	**ELA**	**Reading**
(Intercept)	737.98***	762.81***	772.23***	778.71***	778.38***	804.19***	797.29***	804.25***
	(18.77)	(17.82)	(13.14)	(12.12)	(19.61)	(18.65)	(13.40)	(12.45)
lag.sci	0.12***				0.07**			
	(0.02)				(0.02)			
lag.math		0.10***				0.05*		
		(0.02)				(0.02)		
lag.ela			0.08***				0.05**	
			(0.02)				(0.02)	
lag.read				0.07***				0.04*
				(0.01)				(0.02)
R2	0.07	0.05	0.07	0.06				
Adj. R2	0.06	0.05	0.06	0.06				
Num. obs.	397	397	397	397	397	397	397	397
RMSE	39.27	37.49	26.87	24.86				
AIC					3982.72	3949.52	3654.57	3588.9
BIC					3998.64	3965.43	3670.49	3604.81
Log Likelihood					-1987.4	-1970.8	-1823.3	-1790.5
Num. groups					29	29	29	29
Moran's I	0.208***	0.207***	0.28***	0.288***	-0.06	-0.051	-0.054	-0.055

***p<0.001, **p<0.01, *p<0.05, • p<0.10

Table 4.
Regression Models Explaining Post-Intervention Outcomes Using Spillover Effects Interacted with IC participation

	OLS				Multilevel			
	Science	**Math**	**ELA**	**Reading**	**Science**	**Math**	**ELA**	**Reading**
(Intercept)	779.06***	787.79***	796.21***	802.70***	797.84***	814.40***	812.19***	820.91***
	(26.85)	(25.84)	(18.58)	(17.21)	(28.04)	(26.63)	(19.10)	(17.75)
treat_teacher	-79.14*	-48.36	-46.55•	-46.73•	-37.84	-19.39	-29.39	-32.78
	(37.41)	(35.68)	(26.07)	(24.12)	(39.41)	(37.42)	(26.95)	(25.03)
lag.sci	0.07*				0.05			
	(0.03)				(0.03)			
treat_teacher:lag.sci	0.10*				0.04			
	(0.04)				(0.05)			
lag.math		0.07*				0.04		
		(0.03)				(0.03)		
treat_teacher:lag.math		0.05				0.01		
		(0.04)				(0.05)		
lag.ela			0.05*				0.03	
			(0.02)				(0.02)	
treat_teacher:lag.ela			0.06*				0.04	
			(0.03)				(0.03)	
lag.read				0.04•				0.02
				(0.02)				(0.02)
treat_teacher:lag.read				0.06*				0.04
				(0.03)				(0.03)
R2	0.08	0.06	0.09	0.07				
Adj. R2	0.07	0.05	0.08	0.07				
Num. obs.	397	397	397	397	397	397	397	397
RMSE	39.11	37.47	26.65	24.71				
AIC					3983.67	3950.48	3656.67	3590.66
BIC					4007.51	3974.33	3680.51	3614.5
Log Likelihood					-1985.83	-1969.24	-1822.33	-1789.33
Num. groups					29	29	29	29
Moran's I	0.194***	0.201***	0.265***	0.277***	-0.06	-0.053	-0.056	-0.057

***p<0.001, **p<0.01, *p<0.05, • p<0.10

Table 5.
Regression Models Explaining Post-Intervention Outcomes After Controlling for Individual level performance

	OLS				Multilevel			
	Science	**Math**	**ELA**	**Reading**	**Science**	**Math**	**ELA**	**Reading**
(Intercept)	213.40***	276.17***	241.55***	310.89***	220.65***	270.12***	292.56***	244.44***
	(27.66)	(26.94)	(26.24)	(22.76)	(30.84)	(30.95)	(28.88)	(22.64)
pre_science	0.71***				0.71***			
	(0.03)				(0.04)			
lag.sci	0.03•				0.03•			
	(0.02)				(0.02)			
pre_math		0.67***				0.67***		
		(0.03)				(0.04)		
lag.math		0.01				0.01		
		(0.02)				(0.02)		
pre_ela			0.70***				0.64***	
			(0.03)				(0.04)	
lag.ela			0.02*				0.02•	
			(0.01)				(0.01)	
pre_read				0.73***				0.70***
				(0.03)				(0.03)
lag.read				0.00				0.00
				(0.01)				(0.01)
R2	0.57	0.54	0.57	0.70				
Adj. R2	0.57	0.54	0.57	0.70				
Num. obs.	397	397	397	397	397	397	397	397
RMSE	26.75	26.2	18.25	14.11				
AIC					3719.87	3712.15	3433.2	3241.27
BIC					3739.75	3732.03	3453.09	3261.15
Log Likelihood					-1854.94	-1851.08	-1711.6	-1615.63
Num. groups					29	29	29	29
Moran's I	0.136***	0.112***	0.082***	0.164***	-0.048	-0.037	-0.038	-0.029

***p<0.001, **p<0.01, *p<0.05, • p<0.10

Discussion and Implications

Discussion...

- The **complex systems network** approach employed allows researchers to capture a more comprehensive level of variation at a **systemic level**.
- The study justified the need to measure for **potential contamination** wherein **administrative decisions** or even **parental involvement** may contribute to **group formation**
  - Potential clustering given students' **baseline performance**, and even some **unmeasured indicators** (self-selection) —**threat to causality**.
- The method depicted is **easy** to implement during **group formation** to comprehensively assess for group baseline performance before the intervention is actually implemented.
- **Individual performance** is not enough to control for **spillover effects** (Table 5), which justifies the need to incorporate these indicators

Thank you for your time and attention!

Contact information:
Manuel S. González Canché,
☎: **215-898-0332**, 🖂: **msgc@upenn.edu**
: **@manny_canche**
: **http://scholar.gse.upenn.edu/canche/**
The University of Pennsylvania
🖂: **38 South 37th Street, Stiteler Hall, Room 207, Philadelphia, PA 19104**

Temporary page!

LaTeX was unable to guess the total number of pages correctly. As there was some unprocessed data that should have been added to the final page this extra page has been added to receive it.
If you rerun the document (without altering it) this surplus page will go away, because LaTeX now knows how many pages to expect for this document.