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It Takes a Village

Network Effects on Rural Education in Afghanistan

Matthew Amos Hoover
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This document was submitted as a dissertation in March 2014 in partial fulfillment of the requirements of the doctoral degree in public policy analysis at the Pardee RAND Graduate School. The faculty committee that supervised and approved the dissertation consisted of Harold D. Green, Jr. (Chair), Gery W. Ryan, and Dana Burde.
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To my wife, Dana, without whom this would not be possible.
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Abstract

It Takes a Village: Network Effects on Rural Education in Afghanistan

Often, development organizations confront a tradeoff between program priorities and operational constraints. These constraints may be financial, capacity, or logistical; regardless, the tradeoff often requires sacrificing portions of a program. This work is concerned with figuring out how, when constrained, an organization or program manager can utilize social networks to take advantage of inherent tendencies that will allow a program to thrive. Specifically, this study looked at the playmate networks of children in 31 rural villages of central Afghanistan and how that relational information could improve programming of a rural schooling program.

To accomplish this, a two-stage approach was used, where network structure and composition was estimated using exponential random graph models (ERGMs) and then related to individual child outcomes in math and language performance using multi-level models (MLMs). Unique in this work was translating ERGM parameters to MLM covariates by using the $t$-statistics from network estimations. Results of the MLMs indicated that individual ability drove most of a child’s achievement, however, both network structure and composition were important in explaining children’s academic achievement. Specifically, children maintained many reciprocated ties with other children, though more advanced network structures – such as triadic closure – were not fully developed in the networks. Compositionally, children tended to befriend others of the same gender and similar academic performance (homophily measures). This translated into MLM results of children doing better academically if they were friends with other children of a similar ability.

Ultimately, the primary concern was how network information could improve program management, performance, and ultimately, impact. Key recommendations for utilizing networks included building in playtime during the school day to facilitate tie formation, identifying isolates and working to integrate them into the existing network, creating a “buddy” system for learning within schools that could provide the catalyst for more
complex network structure, like triadic closure, and using visual depictions of networks to identify targeting opportunities for communication within networks.
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Chapter 1

Introduction

How can the effectiveness of a development intervention be improved without additional monetary or labor resources? This is the primary policy question of this study. Regardless of setting, all development interventions face difficulties. Access to sites, understaffing, underfunding, and lack of monitoring all contribute to decreased intervention effectiveness. The consequences of such constraints may or may not be severe; if there are ways to increase the probability of success, how can they be used?

The setting for this study is Afghanistan, where an evaluation of a large-scale, rural, community-based school (CBS) program\textsuperscript{1} found the CBS program to be effective at increasing child enrollment in schools, as well as mathematics and language\textsuperscript{2} skills (Burde and Linden, 2012, 2013). I add to Burde and Linden (2012, 2013) by exploring the effect children’s playmate and friendship networks had on attendance, mathematics, and language achievement. Understanding the structure of children’s playmate and friendship relations allows development organizations to improve aspects of an intervention, like recruitment or implementation. In essence, an organization benefits by using local, self-organizing mechanisms to better ensure an intervention’s success.

\textsuperscript{1}The program was named the Partnership for Advancing Community Education – Afghanistan (PACE-A) and ran from 2006 through 2011, funded by the U.S. Agency for International Development (USAID). However, the evaluation described herein was separate from the PACE-A program and was not funded by USAID.

\textsuperscript{2}While Afghanistan is multi-lingual, in this area of Afghanistan, all language testing was conducted in Dari.
1.1 Afghanistan – A Brief Historical Review

The history of modern Afghanistan dates back to the mid-1700’s when Pashtun\textsuperscript{3} tribes wrested control of the country from Turko-Mongolian conquerors (Rubin, 2002; Barfield, 2010). Pashtuns later reasserted their dominance over the country by ousting the British in the mid- to late-1800s. However, this study is concerned with recent Afghan history, commencing just prior to the Soviet invasion in 1979. In 1978, with the death of Mohammed Daud Khan (President of the Republic of Afghanistan) in the Saur Revolution (in essence, a one-day \textit{coup d’etat} by the People’s Democratic Party of Afghanistan (PDPA), Communist rule overtook Afghanistan. This ushered in 30-plus years of conflict with negative consequences for education.

Unrest against the PDPA rule began when policies to radically transform the rural economy met with stiff resistance (Barfield, 2010). In a little over a year from the Saur Revolution, PDPA support declined and the first Chairman of the Revolutionary Council of the Democratic Republic of Afghanistan, Nur Muhammad Taraki, was assassinated on the orders of Hafizullah Amin, who took over command. Amin’s rule did not last long; within four months, he was assassinated by Soviet special forces and Babrak Karmal was installed in power by the Soviets to restore order to the stumbling PDPA.

By installing Karmal to power, the Soviets signaled their intentions to take a more active role in Afghan affairs, sending in both military and civilian officials. As Barfield (2010) stated, “Using the analogy of their invasion of Czechoslovakia in 1968, the Soviets assumed they could begin withdrawing their troops after a few months when order was restored.” This assessment was far from the case. By 1980, the PDPA was so dependent on the Soviets, a RAND Corporation report stated “the PDPA [was] weaker now than it was before the December 1979 intervention and would probably be swept away shortly after a Soviet withdrawal” (Fukuyama, 1980). Soviet troop strength would eventually rise to over 110,000 (Barfield, 2010) and the Soviets and Afghan \textit{mujahideen}\textsuperscript{4} fought a protracted war until 1989. During the conflict, the United States, Saudi Arabia, and Pakistan all funded and trained the \textit{mujahideen} in their struggle against the Soviets (Coll, 2004); their covert

\textsuperscript{3}Pashtuns are a major ethnic group in Afghanistan, residing primarily in the south
\textsuperscript{4}Mujahideen is an Arabic work for “strugglers” that can be colloquially known as a “freedom fighter.”
support allowed the mujahideen some parity against the overwhelming Soviet military advantage.

By February 1989, the Soviets completed their withdrawal from Afghanistan, leaving a Soviet-friendly government in power headed by Mohammad Najibullah, the former head of Afghanistan’s equivalent to the Soviet’s KGB. Analysts predicted the Najibullah government would fall shortly after the withdrawal (Coll, 2004). Aid shipments, both military and civilian, were still considerable from the Soviets to the Afghan government (Rubin, 2002), propping up the Najibullah regime until the dissolution of the Soviet Union in 1991. In 1992, Boris Yeltsin (Russia’s new president) discontinued aid to the Najibullah regime. Quickly thereafter, the defection of Najibullah’s ally, Abdul Rashid Dostum, from his military post in the government to the Supreme Council of the North (headed by Ahmad Shah Massoud) signaled the end of Najibullah’s reign (Coll, 2004).

As the combined forces of Dostum and Massoud surrounded Kabul from the north, Gulbuddin Hekmatyar eyed Kabul from the south. All were former mujahideen who had fought the Soviets. Massoud and Dostum struck first, gaining many strategic positions around Kabul, while Hekmatyar hastily seized as much area as possible (Coll, 2004). With these moves, a new round of war began, where former mujahideen battled against one another for control of the country. This would last until 1996, when the Taliban seized power across the country, starting in the southern city of Kandahar.

The Taliban\textsuperscript{5} rose to power in 1994, led by Mullah Mohammed Omar (Khalilzad and Byman, 2000). The Taliban first consolidated power in southern Afghanistan in 1994, and in 1995 they captured Herat, an important city in the west of the country (Rashid, 2001). They then turned towards Kabul, which was under the control of Masoud at the time. Having captured Jalalabad to the east of Kabul in a surprise attack, by the end of September 1996, the Taliban entered Kabul as Masoud’s contingent retreated to the north. The Taliban marched on the United Nations (UN) compound in Kabul, which provided safety and protection to former president Najibullah. The Taliban extracted

\textsuperscript{5}Taliban is the Pashto work for “students”; the organization is derived from adherents who were students in religious schools originating in Kandahar, Afghanistan and Pakistan tribal areas on the border with Afghanistan.
Najibullah from the UN, torturing and then executing him (Rashid, 2001).

Though the Taliban pursued Masoud into the Panjshir Valley (Masoud’s home territory), the Taliban were not able to eliminate Masoud or his contingent of forces; Masoud’s forces and the Taliban engaged in insurgent combat in subsequent years. By 1997, with the fall of Mazar-e Sharif in the north of the country, the Taliban effectively controlled and governed Afghanistan (Khalilzad and Byman, 2000; Rashid, 2001). The Islamic State of Afghanistan became the Islamic Emirate of Afghanistan; it was recognized by only three countries: Saudi Arabia, Pakistan, and the United Arab Emirates.

The Taliban, originally thought of as a “traditionalist” force for stability in Afghanistan (Nojumi, 2008), which Afghans accepted (Jones, 2009), turned out to be quite the opposite. After capturing Kabul, the Taliban issued decrees severely restricting women’s rights, instituting punitive punishment for crimes, mandating personal grooming for men, and restricting leisure activities (Rashid, 2001). Women suffered gravely under the Taliban; they were banned from working, severely affecting the health and education systems (Rashid, 2001), forced to wear a burqa, and subject to increasing amounts of violence (Human Rights Watch, 2001). The impact on education was particularly severe – girls were banned from schools after the age of eight and illiteracy rates soared to an estimated 90 percent among young girls (Human Rights Watch, 2001). With educated women comprising a majority of teachers across the country (Human Rights Watch, 2001), boys also suffered declining educational prospects.

While Afghans were dissatisfied with the Taliban, the Taliban destroyed its opposition and created disarray so there were no viable alternatives (Jones, 2009). In fact, by 2001, the Taliban were in control of all Afghanistan other than the Panjshir Valley, which still remained under the control of Masoud. On September 9, 2001 though, Masoud was assassinated by two men posing as journalists (Radio Free Europe/Radio Liberty, 2003). What effects that assassination would have on the Taliban’s plans for complete control of Afghanistan is unknown, as al-Qaeda’s attacks of September 11, 2001 in the United States ushered in the next phase of conflict. On September 26, 2001, CIA operatives

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6 A burqa is a loose fitting garment covering a woman from head-to-toe, with a small mesh grill around the eyes for sight.
arrived to aid the Northern Alliance (Schroen, 2007) and the United States began its military involvement in Afghanistan that continues to this day. The CIA, and then U.S. Army special forces, laid the groundwork for U.S. involvement in Afghanistan in late September 2001 by engaging key Northern Alliance officials (Jones, 2009). By October 7, 2001, the U.S. began bombing key communications and air defense outposts of the Taliban. This was quickly followed by ground fighting between Afghan allies (including Dostum), CIA, and Special Forces against the Taliban in the north (near Mazar-e Sharif), where the Taliban were defeated on November 10, 2001 (Jones, 2009). More quickly than the Taliban came to hold power, they lost it – by December 18, 2001 in the eastern mountains of the country, the Taliban were defeated. However, both Mullah Omar and Osama bin Laden (al-Qaeda’s leader) escaped the siege.

As the reign of the Taliban ended, the restructuring of the Afghan government began. Hamid Karzai, from the Kandahar region, became the interim leader of Afghanistan through the Bonn Agreement in December 2001. Through the 2002 loya jirga, Karzai was affirmed as leader of the transitional government until his election as President of the Islamic Republic of Afghanistan in 2004. Among the humanitarian necessities resulting from war, the new Afghan government was tasked with rebuilding government infrastructure as well as all vestiges of service, like schools, hospitals, transportation systems, and sanitation services. Much of the reconstruction was financed through the efforts of the international community.

To this day, the Afghan government and the International Security Assistance Force (ISAF) are still engaged in combat operations with Taliban and al-Qaeda insurgents across the country. After the Taliban defeat, in the mid-2000’s, a resurgent Taliban began a counter-insurgency campaign that continues to affect security around the country (Giustozzi, 2009). The ongoing combat operations create a fluid environment for reconstruction and development. Development efforts must be conscious of the impact the insurgency can have on their effects. Newly constructed roads, for example, can become primary targets for improvised explosive devices; schools or medical clinics can be bombing targets.

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7A loya jirga is a large meeting of people to collectively agree upon major events, such as the adoption of a constitution or selecting a leader.
It is within this environment that PACE-A began in 2006.

1.2 Development and Education in Afghanistan

Prior to the Soviet invasion, Afghans found “…the 1960s and 1970s as the golden age… of Afghanistan,” (Coburn, 2011) where tourism flourished, as Afghanistan linked Europe with India. Moreover, while still developing, Afghanistan’s economy was showing signs of growth from the early 1960’s through the 1970’s, with gross domestic product (GDP; measured in current U.S. dollars) per capita rising from $55 in 1960 to $247 in 1979 (World Bank, 2012). However, with the commencement of the Soviet invasion, not only did GDP per capita drop in 1980 and 1981 ($237 and $222, respectively), but the next time it was measured (in 2001), it was down to $92. Only in 2006 did Afghanistan regain its GDP per capita level of 1979 (World Bank, 2012). See Figure 1.1.

The effects of the Soviet invasion (and subsequent conflict) on education were equally stark. In 1978, just prior to the Soviet invasion, primary school enrollment was a little more than 800,000 pupils, which accounted for about 35 percent of the school-age children. This was a large increase from estimates 30 years prior, when less than 100,000 students were enrolled in school and the country’s literacy rate was around 8 percent (Gregorian, 1969). By the time the Taliban were deposed in 2001, enrollment was down to about 773,000 pupils, though this only accounted for 19 percent of school-age children in the country (World Bank, 2012). See Panel A of Figure 1.2.

Not only was there an absolute decrease in the number of children enrolling in primary education in the country, but there was a relative (percent of school-age children enrolled) decrease too. After the fall of the Taliban in late 2001 though, the (re-)enrollment of children quickly escalated. In fact, as seen in Panel B of Figure 1.2, gross enrollment of girls in primary school increased from zero percent in 2001 to over 50 percent in just two years; for boys, by 2003, gross enrollment was over 100 percent, indicating that those of age were enrolling in primary school, while older boys were re-enrolling in school (World Bank, 2012).

The international community took an active role in reconstituting Afghan education.
Figure 1.1. Afghanistan GDP per Capita, 1970 – 2011

Note: Dashed portions represent linear interpolation between the previous and subsequent measurements.

However, the environment in which the Afghan government and international community found itself with respect to education in the fall of 2001 was bleak. Taliban dictates against working with the government of Afghanistan, the lack of resources available, like books, and the need to reassert some centralization at the national, provincial, and district level
all created a difficult environment (Sigsgaard, 2009). In describing this fragility, Sigsgaard (2009) states, these were the “...difficult circumstances which education agencies must accept if they wish[ed] to operate in Afghanistan.”

An early program by USAID helped jumpstart work on education reform. USAID paid
to print classroom materials and train teachers (Margesson, 2002), though this was just a stopgap. The curriculum was not reformed for this printing (Sigsgaard, 2009); it was simply to have content available as education began anew under the Karzai regime. By 2003, USAID embarked on a much bigger effort to improve education across Afghanistan.

The Afghanistan Primary Education Program (APEP) was a multi-pronged program designed to accelerate learning (i.e., condense two years of schooling into one for older children), print/distribute textbooks, train teachers, and support the Afghanistan Ministry of Education’s development (USAID, 2005). Programs like APEP were intended to jumpstart the education system in Afghanistan after years of neglect and decline. A State Department audit found that APEP was successful in most of its goals, though it fell short in recruiting female students, textbook distribution, and advancing accelerated learning students (Office of Inspector General, 2005). The implementing partner (Creative Associates International) stated communities’ unwillingness to allow their female children to attend school led to under-enrollment. Addressing a community-specific problem – like low female enrollment – in the context of an intervention can be difficult; however, utilizing the relations within the community may address the problem from inside the community. The objective for an implementing organization then is how to develop, understand, and utilize linkages within a community to positively impact an intervention.

1.3 Intervention Evaluation and Effectiveness

Evaluation is a key component within international development programming. Organizations and independent evaluators employ a variety of methods to evaluate the effectiveness of interventions, such as qualitative methods (Green et al., 2010; Sherman and Strang, 2004; Paluck, 2010), modeling (Berman and Laitin, 2008; Kalyvas and Kocher, 2007; Lyall, 2010), natural experiments (Chattopadhyay and Duflo, 2004; Hyde, 2007; Vicente, 2010), and field experiments (Olken, 2007; Duflo and Hanna, 2005; Beath et al., 2011; Paluck, 2009; Fearon et al., 2009). The use of a particular design depends on the research question.

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8 Accompanying Burde and Linden (2012, 2013), Burde (2012) found parents willing to send girls up to age 12 to school. As girls aged, parents became less willing to send girls to school, but this was not universal in Ghor province or across Afghanistan.
and needs of the evaluation. Qualitative methods can be descriptively informative, but cannot discuss causal or associative impact, due to the unique nature of the program or evaluation (Teller, 2008). However, for nuance and understanding, qualitative work can be incredibly insightful. In Blattman (2009), a quantitative evaluation, the author found ex-combatants from Uganda’s ongoing civil war were more politically engaged than youth who had not fought in the war. Interviews Blattman did with ex-combatants illuminated why: the ex-combatants’ war-time experiences taught them leadership and organization, which they intended to put towards to the benefit of their community, now that they were no longer child soldiers (Blattman, 2009).

Often, direct evaluation is not possible due to variety of factors, such as ethics, safety, or lack of a suitable program to evaluate (Burde, 2012). In these instances, researchers might use modeling as a hypothesis generator or as a precursor to future evaluations. For example, Lyall (2009) explored why conventional military forces would engage in indiscriminate attacks on civilian populaces if it led to great reprisals by insurgents in the Chechen conflict in southern Russia. Due to safety, Lyall modeled results based on historical data and media accounts. Data indicated that contrary to popular opinion, indiscriminate attacks on civilians did not lead to greater reprisals. In this sense, the modeling from Lyall (2009) does not discuss program impact, but provides contextual information an organization could use to implement a program, like reducing violence and harm towards a civilian populace during conflict.

The use of experiments – both natural and field – has increased in international development in recent years. A natural experiment uses naturally occurring variation, such as the allocation of election observers to parts of a country (Hyde, 2007) or the discovery of oil in one, but not another, country that are quite comparable (Vicente, 2010). A field experiment sets conditions that introduce variation for evaluation. Often, these are randomized control trials (RCTs) where a certain group receives a “treatment” and another group does not (the “control” group). For example, in Barrera-Osorio (2006), researchers investigated differences between public and private schools implementing a government-sponsored program to increase school achievement in Colombia.
Often, an RCT will incentivize the intervention being evaluated. In Progresa, a conditional cash transfer program in Mexico that provided family subsidies for medical clinic attendance and school enrollment, Schultz (2004) found children from households which were part of Progresa maintained higher enrollment in primary school than children from non-Progresa households. As Progresa matured into the program Oportunidades, Fernald et al. (2008) found that the Oportunidades RCT was likewise important for child health outcomes; namely, children in an Oportunidades household showed better anthropometric outcomes, including less stunting and higher height-for-age, than children from non-Oportunidades households.

Improving an intervention is crucial to improving outcomes; rarely is an initial design the best – it takes change and improvement to ensure the impact intended, as witnessed in the transformation from Progresa to Oportunidades. Development evaluations do not usually investigate how to increase effectiveness; they often conclude whether or not an intervention is effective. While an RCT may show effectiveness in a controlled environment, what can make that same intervention effective in a less controlled, less monitored environment? This is part of the argument put forth in Lareau (2008) on the limited value of RCTs in education research,9 that “...policy analysts have not paid sufficient attention to the crucial issue of implementing research results,” (Lareau, 2008). Moreover, Lareau states:

Decades of research in education clearly demonstrate that it is not possible for policymakers to mandate the successful adoption of an educational policy. Rather, successful reform requires that educators “buy into” the new policy. ... Promising reforms may be difficult or impossible to implement or “scale up” beyond the initial research setting (Lareau, 2008, p. 146).

While not diminishing the value of RCTs in demonstrating intervention effectiveness, the point of this study is to figure out how to strength RCT effectiveness results outside the

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9Lareau writes of U.S. federal legislation encouraging the use of RCTs in the American education context. While the scope and purpose of educational research differ dramatically between domestic and international contexts, the critique can be applied in either situation.
confines of an experimental situation. In an era of reduced resources and growing development needs, policymakers need ways to increase the effectiveness of proven interventions. As McEwan (2012) states, “...impact evaluations ... are not the only ingredients to policy decisions. Among other factors, the policy decision must weigh the financial sustainability of the policy and political constraints to its effective implementation and scale-up.” In addition to political constraints, addressing cultural constraints are difficult within an experimental framework (e.g., a community’s hesitation to enroll girls in APEP). However, identifying mechanisms to influence a cultural constraint (e.g., identifying a community change agent) may affect an intervention’s implementation in non-experimental contexts for success. Whether done using qualitative methods, modeling, or relying on relational data, utilizing a robust design can strengthen program findings (Burde, 2012).

1.4 Research and Policy Questions

This study aims to understand how the effects of a successful intervention can be enhanced and made robust to non-experimental settings by using the social and cultural aspects of the intervention. Thirty-one villages, 13 of which were in the control group and 18 of which were in the treatment group, were part of an RCT assessing whether CBSs were effective at increasing child enrollment in primary education and increasing achievement in grade-appropriate mathematics and language (Burde and Linden, 2012, 2013). In short, Burde and Linden (2012, 2013) found that an international non-governmental organization’s (NGO’s) implementation of PACE-A increased both enrollment of children in school, as well as achievement, with girls showing differential gains. In addition, distance from the school was negatively associated with outcomes like enrollment, attendance, and achievement (Burde and Linden, 2012). Unexplored, however, were relational data collected on the social networks of children. In this context, relational data were operationalized two ways: first, informal playmate ties, and second, formal friendship ties, between children within rural villages in central Afghanistan.10

In the context of the CBS program, the catchment of the proposed school was a self-contained village. The school draws from the village in which it is situated, suggesting

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10 There are no ties between children across villages.
how children interact with others may impact schooling decisions. Using children’s playmate and friendship networks, I show how structural and relational effects of the networks affected both attendance and achievement in these schools. Structural effects in the network, such as density (proportion of total ties present between respondents) or triads (how the ties between three children are configured), can help one understand how information about the school, or the positive aspects of attending the school, may spread. Moreover, homophily effects, like similarity of attendance or performance indicate how children in the networks might influence each other. For example, if children who enroll in school maintain playmate and/or friendship ties more frequently with other children who are enrolled in school, then homophily may be used to influence some behavior of interest, like greater attendance at school.

Both structural, like density or triads, and relational, like homophily, effects have been found to be important in adolescent networks in education in the developed world (Cappella et al., 2012; Schaefer et al., 2010). Both Lubbers (2003) and de la Haye et al. (2010) demonstrated structural and homophily effects on school-based adolescent networks. Lubbers investigated Dutch secondary schools, while de la Haye et al. researched Australian middle schools. These works provide some context to understand adolescent behaviors within social networks; however, little is known about network effects within developing world educational contexts.

Therefore, I pose three research questions:

1. What are the features of playmate networks’ tie formation amongst children in rural Afghan villages? In other words, what are the network structural effects that govern relationships between children?

2. What social cognitive effects (human-to-human interactions) affect children’s behavior with respect to school performance, controlling for network structural effects? Moreover, are there spatial effects that mediate human-to-human interactions with respect to educational outcomes?

3. How do environmental factors, network structure, and social cognition interact to
affect children’s learning in rural Afghanistan?

Importantly, I am interested in the policy implications of networks on interventions. Therefore, I pose the following policy question for speculation: given results on environmental, structural, and cognitive effects on student achievement, in what ways can social networks be used to strengthen education interventions in the developing world?

While the research questions concern knowledge within Afghanistan, the policy question concerns education policy more broadly across the developing world. Randomized control trials, under which these network data were collected, are frequently implemented in the developing world (Kremer, 2003; Schultz, 2004); so, the question of interest is if relational data provides additional information a government or NGO can use to increase the effectiveness of their education intervention.

Behavioral decisions, for example, have been found to be tied to the relation one maintains with others (Conley and Udry, 2010; Banerjee et al., 2012). For example, Conley and Udry (2010) demonstrated that pineapple farmers in Ghana adjusted their inputs based on what they knew of their peers’ practices. In essence, they demonstrated some simple homophily behavior by adapting an imitation strategy. In Banerjee et al. (2012), looking at the spread of microfinance uptake in rural Indian villages, researchers found that the more central original microfinance loanholders were in the network, the greater the overall uptake of microfinance loans. Central members were able to “diffuse” information about an innovation, whether it be agricultural, as in Conley and Udry (2010), or finance, as in Banerjee et al. (2012). However, to the extent network data have been used in the development realm, it is mostly in terms of centrality or aggregate measures. There may be more complex processes at work, like sub-network processes of learning or dyadic (person-to-person) relationships that are important in affecting behaviors. The value and importance of the relations between actors in the network is lost (cf. Banerjee et al., 2012; Aubel et al., 2004; Angelucci et al., 2010). My approach will retain information at the individual level and explicitly model relations between children within villages.

This approach uses two steps to understand how the effects of a successful intervention can be enhanced and made robust to an non-experimental setting. First, to estimate
network effects, I use a tie-based model that focuses on relations between respondents, asking: “How are outcomes of interest, like enrollment and achievement, related to the ties children maintain amongst each other.” This is estimated with exponential random graph models (ERGMs); it explicitly values the interdependence between actors\textsuperscript{11} in the network (Lusher and Robins, 2013). Second, I use the parameter $p$-values estimated in the ERGMs to estimate a three-level multi-level model (MLM) of environmental, structural, and cognitive effects on children’s schooling outcomes. The levels of the model are children within households within villages, with all outcomes measured at the child level.

Without generalizing results of these estimations, which can be difficult with RCTs (Lareau, 2008), I argue that network structures, like transitivity and reciprocity, are common across various domains (Patacchini and Zenou, 2011; Mihaly, 2009; Christakis and Fowler, 2011) and regions (Angelucci et al., 2010; Lubbers, 2003) of the world, so the argument is not one of generalizability, but how relational data can strengthen the impact of an intervention.

The rest of the dissertation is organized as follows. Chapter 2 presents the conceptual model and reviews literature on how environmental, structural, and cognitive aspects influence educational outcomes. It also presents background on the evaluation conducted and data collected. Chapter 3 provides the methods used in analysis. These include ERGM and MLM estimation procedures as well as model checks. Chapter 4 presents results. I start with descriptive results of the Afghan data at the household, child, and network level. Results from the ERGM/MLM estimations follow, as well as goodness-of-fit diagnostics of the ERGMs. Chapter 5 discusses the implications of the results for practitioners in the field, while chapter 6 concludes. Network graphs for each village appear in Appendix A, while the instruments used in data collection appear in Appendix B. ERGM estimation diagnostics can be found in Appendix C.

\textsuperscript{11}I use actors as a synonym for respondents throughout.
Chapter 2

Background

Children are social creatures, identifying family, friends, and others through deduced cues around them. Family helps instill personal values (Patacchini and Zenou, 2011) though as children mature, they begin to develop behaviors based on their own beliefs and the beliefs of others (Schaefer et al., 2010). Social cognitive theory posits “… human functioning is explained in terms of a model of triadic reciprocality in which behavior, cognitive and personal factors, and environmental events all operate as interacting determinants of each other” (Bandura, 1986, p. 18). Behaviors are not simply a product of one’s own choices; they are based on one’s self-awareness, surrounding environment, and others with whom they have a relationship.

Relationship ties to others are particularly important. Social impact theory is defined as “… the great variety of changes in physiological states and subjective feelings, motives and emotions, cognitions and beliefs, values and behavior, that occur in an individual… as a result of the real, implied, or imagined presence or actions of other individuals” (Latané, 1981, p. 343). The intersection of social cognitive theory, as defined in Bandura (1986) and social impact theory (Latané, 1981) provide the basis for a conceptual framework to understand how children’s cognition, networks, and environments explain educational achievement.
2.1 Conceptual Model

According to Bandura (1986), social cognitive theory defines human functioning through two major influences – the reciprocality of human relations and environmental factors. Reciprocality – or the exchange of information and knowledge between people – of relations can include behavioral, cognitive, and personal factors and are represented through symbolic, forethought, vicarious, self-regulatory, and self-reflective capabilities of an individual. Broadening the reach of the reciprocality capabilities, social impact theory, as defined by Latané (1981), indicates three effects of social relations from person-to-person; namely, social force, a diminishing marginal effect of force, and a divisional effect of force upon an audience. In figure 2.1, I provide a conceptual model of how social cognitive theory, combined with social impact theory, interact to affect behavioral outcomes.

![Conceptual Model – Environmental, Structural, and Cognitive Effects on Behavior](image)

Figure 2.1. Conceptual Model – Environmental, Structural, and Cognitive Effects on Behavior
In the conceptual model, social cognition represents Bandura’s reciprocality as part of social cognitive theory. The various reciprocal capabilities feed into social cognition and represent avenues for how people interpret and react to information from others and the environment around them. Symbolic capability represents one’s ability to take “transient experiences” (Bandura, 1986) and use those to help instruct one’s future actions. In this way, one can take disparate and possibly incomplete information and use it to understand a future scenario. For example, a child may see a sibling attend school; the sibling’s absence from the house is a symbol of the educational experience. A child may use that information to think that to be like their sibling, they too might consider attending school. The symbol of school—a sibling’s attendance—can manifest itself in one’s mind to the intended behavior: personal attendance at school.

Forethought capability—another aspect of social cognition—Involves using future outcomes to motivate current action (Bandura, 1986). For example, if one knows they need to graduate from school to receive a certain job, then motivating oneself to study now to ensure graduation in the future is an example of forethought capability. It may also manifest itself as wanting to do better in the future; for example, if a certain grade on a test was not satisfactory, increasing one’s study to ensure a better outcome on the next test would be emblematic of forethought capability.

The two prior capabilities—symbolic and forethought—indicated action/reaction within an individual. In essence, a trial-and-error process: if one chooses A, then B will, or may, happen. However, the world allows us to learn vicariously from others; hence, a vicarious capability allows one to further model behavior by interacting and observing others (Bandura, 1986). While this may manifest itself in innocuous ways—such as observing a friend being scolded for speaking out of turn in class—it can also be a primary learning pathway. For example, learning to drive a vehicle is best learned—for safety reasons—for observing and learning through others, rather than experimenting with trial-and-error.

Understanding models, reflection, and others’ actions inform one’s own behaviors. Through both self-regulation and self-reflection, one can turn aspects of cognition into
fully-formed self-action. One’s self-regulation capability involves comparing an outcome to one’s own internal standard; that is, does an action measure up to one’s intention, and if not, what is the response. It is a measure of personal will. Harking back to the example of poor performance on a test, an understanding that increased studying may ensure a better grade on the next test is forethought, however, increasing one’s study time is self-regulation.

Self-reflection can be thought of a “summing up” of the rest of the cognitive capabilities as defined in Bandura (1986). Self-reflection involves analyzing one’s experience – symbolic interactions, vicarious representations of a process, and one’s forethought and implementation of a behavior – to gain a better understanding of oneself and the environment around them. For a parent, this could be the long-run experience of their educational endeavors on their thoughts and feelings towards their children’s education. For example, what a parent gained through education may have helped them realize their goals; their reflection on how education helped them reach their goals can symbolize how they want to represent and advocate for education with their children.

Together, social cognition in figure 2.1 represents how others interpret, process, and use information from those around them to inform their actions, and ultimately, behavioral outcomes. An additional component that mediates everyone’s influence is the structural impact of the network in which one is embedded. The use of structural impact is akin to Latané use of the term social impact, where he describes how one’s sociality impacts others – and themselves – within a social network (Latané, 1981).

Latané (1981)’s general theory is reduced to three primary principles; first among them is what I have termed the force effect. This effect encompasses how strongly any particular social effect is felt by someone and is multiplicative in nature, consisting of how strongly the effect is presented, the immediacy between effect and action, and the number of people transmitting (Latané, 1981). In essence, the larger number of people delivering similar information, beliefs, attitudes, or messages, within close social proximity of each other, and nearer the time when a target must take action, the larger the impact on the target’s subsequent actions. For example, the effect of three close friends’ study behaviors

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close to a test likely has a stronger effect on the child’s behavior than ten distant friends’ study behaviors months from a test.

Latané describes two other principles, which I term the diminishing marginal effect and the divisional effect. The diminishing marginal effect states that while the force effect from a multitude of people within a network may increase the target’s likelihood of adapting some course of action, there is a diminishing return to additional messengers (Latané, 1981). That is, the force effect from the zeroth to the first person is greater than the one-hundredth to one-hundredth-first person. In practical terms, this indicates that if ten people tell a child to do their homework, the marginal effect on the child actually doing their homework is greater with the first person and declines marginally from person two through ten. The third principle – what I have termed the divisional effect – indicates that the force effect is diffused amongst the intended target audience, meaning the concentration of the message is dependent on the size of the audience receiving the message (Latané, 1981). For a teacher, this has important implications – the force effect on any particular student in a class is less than if the teacher was working one-on-one with a student.

While Latané used the term social impact in his theory, I have repurposed this to be structural impact within figure 2.1 for the following reasons. The effects of social impact theory – force, diminishing margins, and division – all speak to the structure of relations between actors in the network. For example, the force effect will likely be stronger from a close, intimate friend than from a distant, casual contact. Of course, there are exceptions to this, such as the Granovetter’s “strength of weak ties” argument that states more distant ties are sometimes more beneficial than strong ties, since they can better open different parts of a network to a person, such as when looking for a new job (Granovetter, 1973). However, for something like school attendance or educational achievement – or most other behavioral decisions – the effect of close, intimate contacts will likely prove important.

Moreover, for both the diminishing marginal effect and the divisional effect, there are structural network corollaries that help explain these phenomena. For diminishing marginal effect, the concept of triadic closure is appropriate. Between three people – A,
B, and C – if A is friends with B, and C is friends with B, then it is likely A and C should, or could, be friends. The likelihood of A and C becoming friends increases with that first connection to B; with subsequent connections through actors, D, E, and F, for example, the likelihood further increases that A and C will become friends, but at a diminishing rate than when there was only the connection with B between A and C (Goodreau et al., 2009). With respect to the divisional effect, basic network dynamics, such as the number of people within the network and how fractured the network is (measured by components – or distinct sub-groups of network members of size three or more – and isolates), can account for the how divided one’s message is to others in the network.

Finally, in figure 2.1, the environment encompasses personal, social, and economic factors separate from one’s relationships with others than influence behavioral decisions and outcomes. Namely, individual factors – such as age, ethnicity, or gender – along with social and economic factors – such as household attitudes towards education, father/mother’s career, or household income – also contribute to decision-making. Moreover, environmental factors may influence or structure certain cognitive process (Bandura, 1986) and social impact.

The intersection of social cognitive theory and social impact theory to define a model of behavioral outcomes utilizes both individual and group norms along with network information. With respect to educational outcomes of children in rural Afghanistan, the model parameters will be represented through individual, household-, and village-level variables (environment), network structural variables (structural impact), and network compositional variables (social cognition). Together, these should provide a robust, multi-level view of children’s educational behaviors.

2.2 Literature Review

While research of factors associated with children’s academic achievement is plentiful, the intersection of individual, environmental, network structural, and network compositional factors – especially in a developing world context – is novel. The following literature review addresses:
1. What environmental variables – at the individual, household, and village level – help to explain children’s academic achievement?

2. How has network structure been applied to better understand children’s academic achievement?

3. How does social cognition affect children’s response to education?

Together, these factors are important in building a model that explains children’s academic achievement from a variety of aspects. In addition, I explore how social networks, through the conceptual model in figure 2.1, can be used in interventions to improve outcomes. While little is known empirically about how network interventions can affect individual outcomes, a review of the literature can inform and develop recommendations around the purposeful use of networks to increase the robustness of interventions to non-experimental settings.

2.2.1 Environmental Factors in Academic Achievement

Environment, as defined here, is multi-faceted. It encompasses both the context within which a child is situated and factors at a variety of levels that determine a child’s behavioral outcome. Much has been written on methods in assessing educational achievement within the developing world (Glewwe, 2002; Kremer, 2003). In some early education studies, Glewwe (2002) found better infrastructure and the provision of writing materials positively impacted writing and math outcomes in Brazil, whereas in Ghana, repairing classroom leaks, the use of blackboards, and to a lesser extent, teacher experience improved test scores. In Jamaica, student performance was predominantly affected by teacher characteristics, namely teacher training within the past three years, use of textbooks in class, and regular student testing. Providing eye exams also improved reading scores (Glewwe, 2002). Finally, in India, teachers training performance and years of education predicted student performance, as did quality of the educational facilities (Glewwe, 2002).

These were observational designs and few of them controlled for innate student ability, which could bias the results upward Glewwe (2002). Improving upon these designs would have been a randomized control trials (RCT), which would balance students’ innate ability
across treatment and control groups; moreover, spillover – or the exposure to treatment by unintended groups or individuals – can be mediated with variation at a higher level than the randomization, like the village (Kremer, 2003). For example, using an RCT, educational material was a positive impact on student achievement in Nicaragua and the Philippines (Glewwe, 2002). However, while RCT design is important, formal or informal policies, such as the level to which baseline education is pinned, can strongly influence success and failure. In Kenya, for example, the government’s academic curriculum was appropriate for children of the elite in urban areas, but wholly inappropriate for basic education in rural, remote areas (Kremer, 2003).

While study design is important to correctly measuring educational outcomes, outcomes may look at a variety of factors, such as academic success, attendance, or cognitive growth. Paxson and Schady (2007) focused in on specific influences of cognitive development. Using data collected in Ecuador, authors found that socioeconomic status, child health, and parenting quality were associated with cognitive development (Paxson and Schady, 2007). Specifically, higher socioeconomic status led to increased cognitive development in pre-school aged Ecuadorian children; moreover, there was a differential gain for older children in more wealthy households (Paxson and Schady, 2007). In this context, Paxson and Schady defined socioeconomic status as a combination of household wealth, parental education, and household composition. Moreover, there were no differences between boys and girls, whereas being from a rural household (as opposed to urban) was associated with higher cognitive development (Paxson and Schady, 2007).

Parenting quality, in particular, was strongly predictive of cognitive development. Parents exhibiting less punitive behavior was associated with greater cognitive development, as was being more responsive to children (Paxson and Schady, 2007). Together, results indicated socioeconomic status and parenting quality were strong predictors of cognitive development in developing countries Paxson and Schady.

In Sri Lanka, Aturupane et al. used a variety of data sources to measure the effect socioeconomic, health, and school quality factors had on academic (math, English, and the child’s first language) achievement (Aturupane et al., 2013). They estimated two
separate models. The first was a production function that estimated direct effects on education; the second was a reduced form equation that estimated how indirect effects, such as health and educational inputs, which were endogenous to the measurement of child achievement, affected children’s academic performance.

With the production function, authors found strong, consistent effects for gender, children’s age, whether the child was first-born, and parental (both mother and father) education. Females performed better than males and first-borns performed better than non-first-borns. Increased age, mother’s education, and father’s education all positively impacted achievement. Moreover, additional time spent in private tutoring, greater attendance at school, and educational resources in the house positively impacted achievement. The only health characteristic that was predictive of achievement was greater height-for-age z-scores (Aturupane et al., 2013).

In the reduced form, authors similarly found gender, age, first-born, and parental education were predictive of academic achievement, along with electricity, household expenditures, and parental hope for their children’s education (Aturupane et al., 2013). The effects common to both the production function model and the reduced form were in the same direction; with respect to household level variables, having electricity, greater household expenditures, and greater hope for children’s education were all positively predictive of greater academic achievement.

School-based factors also contributed to academic achievement. Aturupane et al. found being part of a “school family,” having more teaching experience, and conducting parent/teacher meetings were all positively predictive of academic performance. However, attending an all-boys school indicated poorer performance (Aturupane et al., 2013). A “school family” was an informal institution within Sri Lanka where schools tended to band together and share resources and advice amongst teachers and principals. The findings from Aturupane et al. (2013) indicated that parental inputs into the educational process – both in terms of their own education and what they contributed through private tutoring and academic engagement with children – were important. But, a child’s health was also important as were investments, such as electricity or schools banding together to share
In a meta-analysis of 25 studies looking at parental involvement on academic performance, Fan and Chen (2001) found that parental involvement tended to have more globalized effects on student achievement, since effects were stronger for a more robust measure, like grade point average, than for subject-specific measures of achievement, like math or reading. Moreover, the type of parental involvement was important – parental aspirations and direct participation in children’s education were much stronger predictors of achievement than acts such as communication or supervision (Fan and Chen, 2001). This is consistent with Aturupane et al. (2013), which found parental hope for their children’s education was an important predictor of academic achievement. It should be noted, the 25 studies used for Fan and Chen meta-analysis all pertained to U.S. settings.

Academic achievement is not solely measured in terms of test scores or grades. Promotion and retention of children also plays a prominent role. In Senegal, Glick and Sahn (2010) presented evidence of early cognitive measurement on longer-term academic achievement, both in terms of performance as well as retention. With respect to performance, they found gender and household wealth (as proxied by assets) predictive of pre-test (second grade) as well as post-test (testing five years later) performance (Glick and Sahn, 2010). In their analysis, the authors found that girls performed worse than boys and greater household wealth led to better performance. Higher mother’s education was predictive of greater achievement on post-test scores, but not pre-test, potentially indicating a longer-term role for mother’s education on children’s achievement (Glick and Sahn, 2010).

In terms of grade promotion, pre-test performance was highly indicative of grade promotion as was household wealth in expected directions. Moreover, with school fixed effects, greater father’s education predicted further advancement, though teacher experience and the share of female teachers in a school predicted less advancement (Glick and Sahn, 2010). However, for girls, having a female teacher was helpful; the interaction between being a girl and having a female teacher indicated greater grade attainment. Secondarily, Glick and Sahn investigated the impact of grade retention on dropout rates.
They found academic performance on the post-test had a modest effect on school dropout controlling for grade retention; however, the large effect was on household wealth. Coming from a poor household, controlling for retention, indicated a child was much more likely to dropout (Glick and Sahn, 2010).

In Suryadarma et al. (2006), authors looked at correlates of student achievement in primary schools in Indonesia. The majority of Indonesian citizens are Muslim, like Afghanistan; however, Indonesia achieved universal primary school enrollment through extensive school construction in the 1980s and 1990s. With attention turned towards school quality, Suryadarma et al. investigated how student, household, teacher, and school effects impacted student achievement. Using a similar production function specification to Aturupane et al. (2013) and Fan and Chen (2001), they measured performance of fourth graders on an independent, surprise test within school, thereby addressing any “teaching to the test” concerns.

They found that girls perform significantly better than boys in both math and dictation and that the more education one’s mother had, the better one was likely to do in math (Suryadarma et al., 2006). There were strong negative effects for teacher absenteeism, having more “permanent” teachers in the school, and having more female teachers. Indonesian primary schools used civil servants, or “permanent” teachers, whose employment as a teacher was guaranteed and contract teachers who were hired locally by the district leaders on a contract basis (Suryadarma et al., 2006). Regular teacher meetings (at least once over the prior six months) indicated stronger performance. Finally, school facilities were important on a gender basis. Having a functioning toilet was important for girls’ performance; Kazianga et al. (2012) found bathroom facilities had a large impact as well for female students.

Previous literature reviewed environmental factors indicative of academic achievement in public schools; however, the history of informal schooling in Afghanistan should be considered as well. Under the Taliban, educating girls was forbidden, so underground initiatives to maintain schooling for girls evolved into viable education alternatives (Kirk and Winthrop, 2006). In fact, the PACE-A program is an outgrowth of the home-based
education used under the Taliban. As such, community-level indicators – not proven within existing studies – were likely important drivers in student performance, much the way parental aspirations were shown to be important in other work (Fan and Chen, 2001; Aturupane et al., 2013). Kirk and Winthrop (2006) indicated the acceptability of the home-based schooling, as well as mixed-gender classrooms, was the level of trust between teachers (who often come from the village) and families. The bond created access to schooling – especially for girls – that was otherwise impossible (Kirk and Winthrop, 2006).

Burde (2010) expanded upon the concept of the community-based schools in an edited volume regarding violence against schools and education. Attacks on schools, children, and communities was not solely due to Taliban influence; it included criminal activity and ethnic violence as well. Parents cited distance as a key reason for not sending their children to school (Burde, 2010); one of the key findings from Burde and Linden (2012) was that community-based schools reduced distance and increased the probability of school enrollment. Moreover, Burde stated community-based schools decreased risk because symbols of education – like a school – were reduced, since community-based schools were often housed within an existing structure. By situating education squarely within the community – figuratively and literally – increased access for parents, educators, and children (Burde, 2010).

In Burkina Faso, rather than implementing a community-based school model, international donors funded “girl-friendly” school construction (BRIGHT) that increased the amenities found in traditional government schools. These amenities included separate toilet facilities for boys and girls, a lunchroom, take-home food, and textbooks (Kazianga et al., 2012). Authors used a regression discontinuity design to evaluate villages that received BRIGHT schools with those that did not at the cutoff criteria for a village’s eligibility, as set by the Burkina Faso Ministry of Education (Kazianga et al., 2012). Theory states villages around the cutoff are very similar to one another except in respect to receipt of the BRIGHT schools, therefore making valid comparison groups.

Kazianga et al. estimated positive effects of BRIGHT schools on enrollment and
achievement (as measured by test scores). Moreover, there was a differentially positive effect for girls in terms of enrollment, indicating school facilities were an important driver of willingness to enroll girls in schools (Kazianga et al., 2012). There were no differential effects, however, between boys and girls on test scores. In a subsequent cost-effectiveness analysis, authors find the BRIGHT school construction to be in the mid-range of interventions discussed in previous intervention reviews (Glewwe, 2002; Kremer, 2003, cf.).

In Burde and Linden (2012, 2013), authors employed a randomized design, allocating the receipt of PACE-A to villages (randomization at the village level). They controlled for a variety of individual- and household-level variables, including gender and age of children, length of time the family lived in the village, ethnic makeup of the family, head-of-household occupation, age, and education level, size of the household, socioeconomic indicators (amount of land and number of livestock owned), and distance to nearest non-community-based school (Burde and Linden, 2012, 2013).

PACE-A successfully increased enrollment and achievement (Burde and Linden, 2012, 2013). Moreover, there were strong gender effects; girls enrolled schools at a higher rate than boys, effectively eliminating the gender gap in enrollment in treatment villages. Similarly, girls outperformed boys on math and language achievement tests (Burde and Linden, 2012, 2013). However, while girls showed differential gains in enrollment and achievement to boys, results also indicated that as children aged, boys were more likely to enroll than girls (Burde and Linden, 2013). Given detailed geographic information on each household in each village, as well as the location of community-based schools and other government schools in the area, Burde and Linden were able to estimate that prior to PACE-A the distribution of households’ distance to the nearest government school in treatment and control villages was roughly equal (Burde and Linden, 2012). After the implementation of PACE-A, households in treatment villages clearly had closer access to schools (by about 2.7 miles), which had important effects for girls. For each mile increase from school, there was a roughly 13 percent decrease in enrollment overall; however, the decrease in enrollment for girls was even more stark: roughly 18 percent (Burde and Linden, 2012).
Previous literature used enrollment or achievement in school as outcomes, though behaviors – such as connectedness to one’s school – may also be appropriate. In McNeely et al. (2002), authors investigated what factors contributed to students feeling “connected” to their U.S. middle or high school under the premise that being connected to support and resources like a school is protective against a range of negative behaviors like substance use and violence. They found that being in a school with more than 80 percent Latino students increased feelings of school connectedness, but a harsh disciplinary climate, being in a larger school, not being involved in school extracurriculars, and having behavioral difficulties in class led to less connectedness with school (McNeely et al., 2002). Teacher qualifications and school setting had no association with school connectedness.

While previous literature discussed individual, familial, and community predictors of educational outcomes, network effects also impact educational outcomes. In a cohort study children from Scotland originally conducted in the 1950’s, Almquist (2011) investigated the relationship between school and individual network effects on minor psychiatric disorder in childhood. Minor psychiatric disorder in this context was meant to represent behaviors such as restlessness, getting into fights, being solitary from others, or having poor concentration (Almquist, 2011).

Looking at over 13,000 children across 524 school classes, Almquist used two levels of network measures as explanatory variables in a logistic, multi-level model. First, at the school level, were network measures, including degree centralization, or how concentrated ties between children in class were amongst certain individuals, proportion of reciprocated ties between children (where both children in a dyad said they were linked to the other), and the proportion of isolates (children that had no ties to others) in the class. Second, at the individual level, Almquist measured how “popular” (degree centrality) a student was based on the number of ties they sent and received, and whether one’s ties were reciprocated between children. Ultimately, the author found that being less central (degree centrality) was predictive of minor psychiatric disorder; moreover, being a female was protective of disorder, but being in a higher grade was more likely to indicate disorder (Almquist, 2011).
Almquist’s demonstration that network effects – at both the school and individual level – predicted behavioral outcomes indicates personal characteristics alone cannot explain all variation in an outcome. For example, teacher effects across classrooms may have been important to both measures, especially as teachers rated children’s level of psychiatric disorder (Almquist, 2011); moreover, higher order network effects – such as transitivity – likely accounted for variation, though it was unmeasured in the author’s model.

Jackson et al. investigated the role of teacher race and class racial makeup on how children perceived each other in class. Children were asked to nominate who they “liked most,” “liked least,” “believed fought,” and thought was a “leader” (Jackson et al., 2006). Each child was given a proportion score on each of these dimensions based on their received nominations divided by the total number of nominators; a fifth measure – social preference – was calculated as the “liked least” score subtracted from the “liked most” score (Jackson et al., 2006). Next, using a multi-level model of children (1,268 total) in classrooms (57 total), the authors investigated how the child’s race and a child’s race/racial composition of the class (or race of the teacher) interaction predicted each of the dimensions described above. In practical terms, children and teachers were either white or African-American.

Results indicated that African-American children were less likely to be a leader but more likely to fight; however, when in a class with more African-Americans, their propensity to be liked the most, and be a leader rose, while the propensity to be liked the least and fight decreased (Jackson et al., 2006). Results were similar when children’s race and teacher’s race were interacted. Interestingly, both race and network composition were important environmental variables. Though Jackson et al. (2006) did not investigate the structure of the relationships between children, they do present evidence of network-based effects on outcomes in the educational setting.

In Cohen-Cole and Fletcher (2008), authors presented a rebuttal to a widely cited study by Christakis and Fowler (2007) that showed obesity spread through social networks. Cohen-Cole and Fletcher took issue with the potential of selection effects and confounding, as well as the role of endogeneity in the networks/obesity link. Christakis and Fowler treated individuals’ behavior changes as a network effect of others’ behaviors’
however, Cohen-Cole and Fletcher posited the change was really an endogeneity issue, best controlled through a better model specification. Replicating the Christakis and Fowler (2007) analysis of the Framingham Heart Study\textsuperscript{1} with the National Longitudinal Survey of Adolescent Health\textsuperscript{2} data, Cohen-Cole and Fletcher (2008) found similar effects; however, once controlling for a more robust set of environmental factors and better accounting for selection effects, they found the association between networks and obesity non-significant (Cohen-Cole and Fletcher, 2008). Ultimately, while networks may contribute to understanding environmental associations on behavioral outcomes, care must be taken not to overestimate associations between networks and outcomes.

### 2.2.2 Network Structure’s Association with Behaviors

Children's social learning is a function of knowledge transfer from adults and peers. In Patacchini and Zenou (2011), researchers investigated the intergenerational transmission of religious values from parent to child. They measured the level of religiousity in a child's network and how this mediated parental influence. Using a linear modeling approach, they found religious parents complemented religious peer effects; both parents and peers helped transmit similar levels of religion to the child. For non-religious parents, they found substitutes between parental effort and peer effects. As the proportion of their child's friend who were not religious increased, parents exerted less effort in transmitting religion to their child. In many ways, parents' efforts – whether religious or not – were done to support the child as they developed in their mold.

As children age and make their own decisions, families still play an important role in the child's life through adolescence and beyond. In rural Thailand, Verdery et al. (2011) investigated the co-mingling of social and spatial networks. By matching up kin, graded

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\textsuperscript{1}The Framingham Heart Study is a long-term longitudinal study of people from Framingham, Massachusetts that has contributed a wide variety of knowledge about heart and cardiovascular disease. Moreover, the longitudinal and comprehensive nature of the study has allowed researchers to investigate a multitude of other physical and social phenomena.

\textsuperscript{2}The National Longitudinal Survey of Adolescent Health (Add Health) is a nationally-representative study of adolescent health and risk behaviors run by the University of North Carolina, Chapel Hill. Four waves of data have been collected starting in 1994/1995 with the most recent wave collected in 2008/2009. Most importantly for network research, in-school network ties were collected from respondents in the sample. The study has been important in understanding adolescent health risk behaviors, social networks, and longitudinal development.
from close to distant, in dyadic pairs and overlaying geographical position of households, they found that kin lived closer to one another than non-kin, on average. For example, 77 percent of those one degree removed from the respondent (e.g., husband/wife, immediate children, biological mother/father) lived in the same household (Verdery et al., 2011). One would expect that the vast majority of young children and spouses co-habitate, though this included adult children as well as parents of adults. Moreover, 78 percent of second-degree kin (biological siblings, step-parents, grandparents), 67 percent of third-degree kin (siblings-in-law, biological aunts/uncles, nieces/nephews), 66 percent of fourth-degree kin (in-law aunts/uncles, cousins), and 56 percent of fifth-degree kin (cousin’s child) lived within 500 meters of the respondent, on average (Verdery et al., 2011).

This indicates a remarkably high amount of correlation between social and spatial networks, where the social network is defined through kinship ties. While Verdery et al. (2011) did not investigate how the kin/spatial networks affected respondents’ behavior, in Mexico, Angelucci et al. (2010) did. Within the framework of PROGRESA\(^3\), a conditional cash transfer (CCT) in rural Mexico where cash payments to families were conditioned on certain behaviors like children’s school attendance or medical check-ups, researchers investigated how kinship ties affected secondary school enrollment of children. To create ties between respondents in the PROGRESA data, researchers used patrilineal and matrilineal surnames of households within villages indicating whether a household was connected to a family network or isolated (in the sense that they have no kinship households in their village) (Angelucci et al., 2010).

Using linear modeling with dummy variables for PROGRESA eligibility, village-level implementation, and village kinship ties, researchers estimated the impact of family networks on secondary school enrollment. They found school enrollment increased for households who were connected to kin in the village, but not for isolated households (Angelucci et al., 2010). They posited that connected households could share resources between households, so even if one’s household did not qualify for PROGRESA, they benefited

\(^3\)PROGRESA was intended as a social assistance scheme for households with children under the age of 5 or with pregnant/lactating women that qualified. Qualification was done based on a poverty index; about half of all households qualified. In general, the program was viewed as a success, expanded, and renamed Oportunidades.
from a sibling’s inclusion in PROGRESA through the reallocation of new and existing assets within the kin network.

These studies indicate the importance family and kin can have on a child’s social network, both directly and indirectly. While Patacchini and Zenou (2011) demonstrated how children’s networks influence family behaviors, both Verdery et al. (2011) and Angelucci et al. (2010) indicate the strong effect family networks can have on children’s behaviors. However, children are adept at evolving their social networks on their own (Corsaro and Eder, 1990). This process started as early as preschool, as children worked through basic network structures, such as reciprocity and transitive closure, and evolved as children meet other children in preschool (Corsaro and Eder, 1990; Schaefer et al., 2010). As children age, they seek out individuals like themselves, which is termed homophily. As Patacchini and Zenou (2011) demonstrated, children chose to associate with other children who demonstrated similar feelings towards religion; in this case, religious homophily.

Beyond family, neighborhoods can play an important role in shaping and determining adolescent behaviors. However, defining neighborhood boundaries has been a difficult proposition (Grannis, 2009). In Hipp et al. (2011), authors took a novel approach – looking at the density of social ties – to form neighborhoods. This ontology allowed for a socially- and geographically-defined “neighborhood” since even in adolescence, most ties are geographically bounded, but often not by the arbitrary borders used to define a geographic neighborhood. Using data from North Carolina schools, authors estimated a multilevel model to determine the intraclass correlation between neighborhoods and ties. Results indicated that using social ties was important in helping to define the neighborhoods, more so than just geography. Moreover, when kids were allowed to be part of multiple neighborhoods, they tended to be part of the same neighborhoods (so crossover was not differential) and streets fostered ties via bus routes. This aligns with research from Grannis (2009), who found that streets can be important conduits of neighborhoods and ties between people in them.

Though not specific to children, Christakis and Fowler (2007) took a novel approach to investigating obesity, using one’s social network as a predictor for obesity. They found
a “three degree” effect, whereby those within three steps from oneself (e.g., friend, friend’s friend, and friend’s friend’s friend) affected one’s obesity level (Christakis and Fowler, 2007). They used the Framingham Heart Study data and traced ties between people’s family and friend contacts over a 32 year period. Interestingly, they found that social closeness as opposed to spatial closeness was an important factor in the spread of obesity; namely, a close friend four states away was more relevant to one’s weight gain (or loss) than a neighbor. Moreover, their results indicated a role for the type of relationship between two people. If the friendship was mutual between two people (i.e., both people named the other person as a friend), the risk for obesity increased even more than if the relationship was asymmetrical (Christakis and Fowler, 2007). The structure of mutual relationships indicates symmetry in relationships is important in understanding how people influence one another. However, Christakis and Fowler faced heavy criticism for methods and results; see Cohen-Cole and Fletcher (2008).

In Neal and Cappella (2012), authors investigated the role network position plays in relational aggression between children. Relational aggression – as opposed to overt aggression – involves aggression through social contact, like spreading rumors about someone (Neal and Cappella, 2012). Neal and Cappella (2012) posited relational aggression was moderated by a person’s connections to less well-connected peers; namely, aggressive peers tended to be more “popular” though their peer relations were less popular. Therefore, relational aggression maintained a power imbalance between socially-connected peers. Using data collected in second through fourth grade classrooms of predominantly African-Americans, the authors used cognitive social structure to identify peer relationships. Cognitive social structure (Krackhardt, 1987) involves respondents stating the relationship between each dyad in the group; in this case, for each child-to-child pairing in the classroom, the respondent stated whether they “hung out” (Neal and Cappella, 2012). Relationship information was aggregated into one set of dyadic relations per classroom.

They found affiliation with poorly connected peers was predictive of relational aggression, though the count of one’s relationships was not (Neal and Cappella, 2012). However, when the count of relations was interacted with the type of relation (affiliation with poorly
connected peers), Neal and Cappella found a significantly positive effect, indicating more relationships with less well-connected peers was associated with relational aggression (Neal and Cappella, 2012). This effect held even after controlling for a number of covariates, including children’s gender (girls were significantly more likely to exhibit relational aggression) and overt aggression. Ultimately, authors indicated network structure was an important part of a complex process that explained a child’s behavior. While many children were relationally aggressive, of concern were popular kids who structured their ties to marginalized children, exploiting a power dynamic in the relationship.

Similar to Schaefer et al. (2010), Daniel et al. investigated network structure of preschool children’s affiliative ties. They observed children in 19 classrooms in Portugal, ranging in age from three to five (Daniel et al., 2013). Similar to Schaefer et al. (2010), ties were observed based on interactions between children at set points in time; however, Daniel et al. used exponential random graph models (ERGMs) to model classrooms cross-sectionally. After fitting a model for reciprocity of ties, popularity, activity, and transitivity, as well as compositional terms (gender homophily as well as sender/receiver effects for gender), they used meta-analysis to understand the importance of the ERGMs parameters across classes. They found significantly more reciprocity among preschool children’s networks than one would expect by chance, as well as a few children in each class that were frequently sought to spend time with (Daniel et al., 2013). Moreover, children tended to seek similar numbers of other children to spend time with and close triangles; that is, become the friend of friend (Daniel et al., 2013). There was less consensus across the grades in terms of the compositional measures.

Daniel et al. (2013) provided evidence of network structural effects in children’s relations. Early on, children sought others for companionship and affiliation; quickly, the “cascading effects” that Schaefer et al. (2010) discussed became evident. In Daniel et al. (2013), authors provided additional evidence of network structural effects in young children’s social relations. Gender homophily indicated as well that others significantly impact one’s own actions and behaviors.

Daniel et al. (2013) also fit a twopath term, which is a precursor and control for transitivity.
While Schaefer et al. (2010) and Daniel et al. (2013) estimated network effects, others sought to control for network structure and composition. In Bramoullé et al. (2009), authors identified exogenous, endogenous, and correlated effects when estimating peer effects. In this context, exogenous effects were akin to how peers influence one’s actions – what Schaefer et al. (2010) termed influence in their longitudinal network model – whereas endogenous effects were akin to sender/receiver effects that Daniel et al. (2013) modeled in their ERGM. Correlated effects were another term for homophily, which both Schaefer et al. (2010) and Daniel et al. (2013) included in their models.

Bramoullé et al.’s used a two-staged least-squares approach to isolate peer effects on participation in after-school recreational activities using the Add Health data (2009). They found participation in recreational activities decreased with age and girls were more likely to participate than boys; moreover, having working parents was also indicative of participation (Bramoullé et al., 2009). Finally, having older female friends was associated with a decrease in extracurricular participation, indicating a peer effect on top of one’s own propensity towards an activity.

While Bramoullé et al. were able to estimate predictors of one’s participation in extracurricular activities, they controlled for all network influence on behavior. So while Bramoullé et al. (2009) were unable to demonstrate the important network structures in their specification as Daniel et al. (2013) did, Bramoullé et al. were able to demonstrate predictors of particular behavioral outcomes that Daniel et al. could not. Schaefer et al. (2010) were able to demonstrate both network effects and predictors of behavior, but only through a longitudinal model. This gap at the cross-sectional level leaves room for methodological and empirical exploration with respect to understanding how networks and other predictors are associated with outcomes.

Social networks are based on perception – the perception of who is a friend or associate, the perception of who is popular and who is not, and importantly, perception of dynamics in a social network. In Cappella et al. (2012), authors investigated predictors of child agreement on peer relations within a classroom. Within thirty mostly African-American, mostly low-income classrooms, researchers asked children to identify who “hung out” with
whom in class (Cappella et al., 2012). Authors aggregated this information, then calculated the Jaccard coefficient per child – a measure of agreement similarity between personal network observations and those of the class. The child’s Jaccard coefficient was used as the outcome in a multi-level model with predictors at the child and class levels.

Significantly, a child’s centrality, class size, and network density were important predictors of agreement on social relations (Cappella et al., 2012). Both network centrality (an individual measure of how connected a child is to other children) and network density were positively associated with child agreement with the class peer network, indicating children who were connected to more peers more closely identified with the actual network configuration of the classroom, while a more dense network predicted better child/class network agreement overall (Cappella et al., 2012). Ultimately, Cappella et al.’s work shows network structure is important in understanding how individuals within a network perceive the network as a whole. More central members are better attuned to the overall network structure; however, density of the network as a whole is also important. Factors at both the individual (centrality) and network (density) levels were important in understanding structure of the network as a whole.

In Haynie (2001), network density and degree centrality were also used as predictors to understand adolescent delinquency. Using the Add Health data, Haynie (2001) investigated how peer delinquency was related to one’s own delinquency, controlling for network structure, as well as how network structure moderated peer delinquency on one’s own delinquency. Prior, peer delinquency was hypothesized to be positively associated with one’s own delinquency, but these results relied on self-reports of peers’ delinquent behaviors, which was subject to measurement error (Haynie, 2001).

Haynie used both the in-school and the in-home Add Health data in her work. The in-home survey – a randomly selected subset of adolescents surveyed during the in-school survey – generated the outcome variable through a series of 14 detailed questions on one’s own delinquency behaviors. The in-school survey provided peers’ delinquency as well as the structural and compositional information used in analyses. Given the sparse amounts of delinquent behaviors and the nested research design (children within schools), Haynie
(2001) opted for a random effects negative binomial model, which accounted for school
differences (random effects) and the skewed distribution of the outcome variable (negative
binomial distribution).

While peer delinquency was positively associated with one’s own delinquency, network
structure (density, centrality, and in-degree, or popularity) was not itself associated with
delinquency. However, the interaction of network structure with peer delinquency pro-
duced significant effects, indicating that network structure moderated peer delinquency
and its effect on one’s own delinquency (Haynie, 2001). Network density had the strongest
such effect. Haynie demonstrated that network structure – similarly to Cappella et al.
(2012) and Patacchini and Zenou (2011) – could influence outcomes within a linear re-
gression framework. However, the constraint on this approach was the lack of structural
features available for modeling. Each of the terms included were dyad-independent, mean-
ing the structural parameter must be wholly dependent on the individual alone; in this
manner, terms like transitivity, which are dependent on the ego and alters, cannot be
included. So while Haynie provided evidence of network structure’s importance, it is less
comprehensive than the work of Schaefer et al. (2010) or Goodreau et al. (2009).

Lubbers et al. (2010) investigated peer acceptance across Dutch classrooms over a two
year period. They found stable and unstable classrooms (with respect to class compo-
sition) exhibit similar levels of peer acceptance, but norms and values as children enter
middle school changed (Lubbers et al., 2010). Moreover, homophily effects of attending
the same elementary school dissipate over time at middle school with respect to peer ac-
ceptance, as did gender homophily, though the tendancy still remained strong (Lubbers
et al., 2010).

Lubbers et al. analysis expanded upon existing methods for networks and associated
effects. Prior, one could investigate network structure or predictors of behavior; with
longitudinal network models (stochastic actor oriented models, or SAOMs), one accom-
plishes both. For example, earlier work hypothesized that girls would be more likely that
boys to display positive effects for transitivity, but Lubbers et al. (2010) demonstrated no
differential effects between boys and girls on transitivity. Their analysis extends the realm
of network analysis with respect to structure, while still retaining an ability to explore individual, group, and interaction effects on behavioral outcomes.

Similar to Lubbers et al. (2010), Alatas et al. (2012) sought to aggregate information across networks. They tried to determine if basic network measures, such as degree, clustering, eigenvector centrality, and path length could provide information on the accuracy of people’s ability to determine the rank ordering of wealth in a village. The ultimate goal was to identify if networks could be used in community assessment and improve targeting of anti-poverty programs in Indonesia (Alatas et al., 2012). Their results indicated that more highly connected households in a village were more likely to accurately report wealth rankings of village households. Moreover, being part of the primary cluster of households in the village and decreasing distance between their household and any other household in the village was also predictive of more accurate village wealth reporting (Alatas et al., 2012).

While Alatas et al. determined network information in conjunction with community targeting of anti-poverty programs was beneficial in ensuring programs reach intended recipients across 631 villages sampled (Alatas et al., 2012). There were weaknesses to their design. First, they considered only dyad-independent measures; this limited their ability to describe more nuanced structural properties that may assist in understanding how program targeting mechanisms work through networks. Moreover, they sampled households within villages to construct village-level networks, potentially leading to bias with respect to network structure (Robins et al., 2004; Gile and Handcock, 2006). Completing a network assessment within all 631 villages may have been prohibitive along a number of dimensions and the sample size was still likely large enough to understand network dynamics within the context of an anti-poverty targeting approach (Alatas et al., 2012).

The endogeneity of one’s socialization ability confounds understanding of basic network structures. However, preschool often represents the first time a child has an opportunity to evaluate, make, and develop friendships in a social setting. Therefore, Schaefer et al. (2010) observed children (ages three to five) in preschool as they started to form their own relationships prior to developing differential socialization skills. Moreover, Schaefer
et al. looked at this network formation over time, focusing on temporal spacing of network structure, such as reciprocity, popularity, and transitive closure. They found a definite order to children’s friendship formation. First, a child reciprocated friendship with another child. Next, as children started accumulating friendships, popular children emerge (receivers of friendship nominations). Finally, as relationships between multiple children occurred, Schaefer et al. (2010) witnessed the formation of transitive closure, whereby friends of friends became friends. Ultimately, Schaefer et al. (2010) provided nuanced information on network structure and formation, how structures built upon each other over time, and avoided the endogeneity of socialization.

In Calvó-Armengol et al. (2009), authors used a person’s network position (in the Add Health data) as a predictor of academic achievement; their specification used the Katz-Bonacich centrality measure instead of degree. Unlike degree centrality, the Katz-Bonacich measure utilized both direct and indirect connections a person has in determining centrality to the network; in essence, for the Katz-Bonacich measure, it was not just to whom one is connected, but to whom their connections were connected that matters (Calvó-Armengol et al., 2009). The authors find that not only was the Katz-Bonacich measure important in predicting academic achievement, it outperformed other measures of centrality in identifying peer effects, such as degree, closeness, and betweenness centrality measures (Calvó-Armengol et al., 2009). These results were confirmed in Mihaly (2009), who also used the Add Health data and measured student achievement across a range of centrality measures.

Calvó-Armengol et al. concluded that the use of other centrality measures was an ad hoc choice, whereas the use of Katz-Bonacich was rooted in prior theory; that is, the Katz-Bonacich centrality measure is proportional to the Nash equilibrium of a multi-player game (Calvó-Armengol et al., 2009). However, in Mihaly (2009), the author believed that selection bias might be an issue and therefore, the centrality measures would be biased in their estimate on achievement. Mihaly instrumented on sociodemographic characteristics of individuals, interacted with grade/gender mean of the individual’s school. Results of the instrumental variables (IV) regression still produced significant effects of centrality.
on achievement, but in the opposite direction; that is, those who were more popular performed worse in school (Mihaly, 2009). This switch in signs may be an indication of true bias in centrality measures, though the author concludes that it is unknown why the sign of the effect changed.

While both Calvó-Armengol et al. (2009) and Mihaly (2009) utilized a centrality measure better rooted in theory (Katz-Bonacich centrality), to understand peer effects in educational achievement, Mihaly’s IV regression lead to an unexplained switch in effect of centrality on achievement. This may be due to bias or poor instrumenting or it may be due to unobservables, such as dyad-dependent network structure that was not captured in the model. Utilizing a model that incorporates dyad-dependence may better estimate centrality’s influence on peer effects in education.

Harassment in school is a product of social norms that allow or encourage the behavior; therefore, there is opportunity to change norms. In Paluck and Shepherd (2012), the authors study children in a school network over time to understand behavior change around harassment. They worked through social referents – or those that were referred to by others (clique leaders or popular kids) – by randomly assigning individuals to the intervention (a training from the Anti-Defamation League on how to confront prior prejudices and influence harassment behaviors of others) prior to a school assembly in the fall with reminders about the training throughout the year (Paluck and Shepherd, 2012). Authors used linear modeling on the program dosage to social referents with fixed effects for children in the school; a secondary IV (where treatment assignment served as the instrument) approach was also estimated. They found some behavior change; namely, teachers were more likely to say students more heavily tied to intervention referents were students more likely to stand up against harassment; these same kids had less disciplinary issues and were more likely to show public support, by buying an anti-harassment wristband (Paluck and Shepherd, 2012). The authors indicated that network position was important in affecting behavior change. By being connected to others who received training on behavior change influenced one’s behaviors. And, the stronger one’s “dose” (the number of connections to social referents), the stronger the effect.
Alexander et al. (2001) found school context was an important predictor in smoking status amongst American adolescents. Using the Add Health data, they used a number of constructs to represent adolescents’ social networks: popularity (raw in-degree), percentage of one’s network who smokes, and whether one’s best friend smokes (Alexander et al., 2001). Using logistic regression to estimate the odds of current smoking across 13 of the Add Health schools, they found a social network comprised mostly of smokers or having a best friend who smoked increased the odds an individual was also a smoker (Alexander et al., 2001). Moreover, when school-level smoking prevalence increased the odds of being a smoker increases (Alexander et al., 2001). Most interesting though, for adolescents who were popular and in a higher smoking prevalence school, there was an even greater chance they were smokers, indicating definite peer processes, though the cross-sectional nature of the data could not determine the selection or influence effects (Alexander et al., 2001).

### 2.2.3 Social Cognition – Moving Beyond Network Structure

While most network studies utilize one analytic approach, Valente et al. (2009) utilized both multi-level models, which estimates predictors of a behavior, and ERGMs, which estimates tendencies in ties between actors. In this case, authors used in-school surveys in Los Angeles with 11 to 15 year olds and collected height and weight information; they then calculated each child’s body mass index (BMI) (Valente et al., 2009). Using the multi-level model of children within schools, they found being overweight was associated with being male, young, having poor school performance, less positive meaning towards physical activity, more positive family social support, and friend’s BMI (Valente et al., 2009). When data were modeled using ERGMs (each class – 15 in total – fit with a common model), there was a strong weight homophily effect. Moreover, overweight children sent more ties than non-overweight kids (Valente et al., 2009). So while the multi-level model indicated predictors of obesity, the ERGMs indicated that there are clear network effects present as well, identifying a role for both structure and covariate predictors with respect to a behavioral outcome.

In a longitudinal study of parents and children in Avon, England, Burgess et al. (2011) investigated homophily tendencies in the friendship networks of children. They
found significant achievement homophily in school (grades, IQ, and going to university), as well as in popularity and bad behavior (Burgess et al., 2011). These homophily effects indicate children were preferentially attached to those like themselves with respect to not only achievement, but also behaviors. The authors used linear modeling with individual fixed effects for “real” friends children selected as well as “simulated” friends, to account for differential pools of friends children had to select from (Burgess et al., 2011). By simulating friends for the analyses, authors were trying to equalize the pool from which children could select friends, to adjust for a low response rate (≈ 40 percent).

Lubbers (2003) looked at 57 classroom social networks of children in the Netherlands, emphasizing homophily behaviors. Given the strong gender homophily within these junior high classes, the author separated each class into a girl and boy network, retaining only ties within gender (Lubbers, 2003). Corsaro and Eder (1990) discussed theory for and against analyzing boys and girls networks separately; ultimately, empirical practicality – as in Lubbers (2003) – is probably the best way to treat gender separation of networks. The purpose of Lubbers’s work was to demonstrate how social effects can supplement more traditional individual effects in understanding behavior.

First, Lubbers (2003) fit a social selection $p^*$ model\(^5\) that fit ties, reciprocity, popularity, activity, transitive closure, and generalized exchange as structural parameters; all effects other than popularity were significant (Lubbers, 2003). These networks demonstrated fewer overall ties, more reciprocity, a cap on the amount of activity, tendencies towards transitive closure, and less generalized exchange than one would expect by a random assortment of ties. When dyadic attributes were added to the structural models – elementary school, performance, and ethnic homophily – only having attended the same elementary school was significant (Lubbers, 2003). That means, for a given pair of nodes, they were more likely to be tied if they attended the same elementary school together. Moreover, for girls, there was a significant homophily tendency on academic performance that was not seen for boys (Lubbers, 2003).

\(^5\)The $p^*$ model is an initial version of ERGM, where the pseudo-maximum likelihood was estimated for a network based on a logit model, rather than estimating the maximum likelihood via Markov chain Monte Carlo methods. Use of the $p^*$ model has been replaced with the use of ERGMs due to better statistical properties.
While many school-based network studies have looked at performance homophily of children in school, de la Haye et al. (2010) applied ERGMs to school friendship networks to investigate obesity between friends in Australia. Their purpose was to understand structure and relationships to better prepare interventions that address both individual- and social-level effects around obesity (de la Haye et al., 2010). Similar to Lubbers (2003), de la Haye et al. (2010) split networks between boys and girls and authors found strong structural effects (reciprocity, popularity, activity, transitive closure, and the propensity for those who send ties to also receive them).

With respect to shared behaviors, they found children who indulged in high calorie food to be friends with others that engaged in the behavior and those involved with organized physical activity to be friends with like-minded individuals within the boy networks (de la Haye et al., 2010). Girls showed homophilous tendencies with respect to organized physical activity and time spent watching television, movies, or playing computer games (de la Haye et al., 2010). Similar to Paluck and Shepherd (2012), results could be used to identify where and how to intervene within a network; in this case, to stem the rise in obesity amongst children.

Children often model their behavior based on those around them; that is, their behaviors and attitudes conform to intragroup tendencies (Paluck, 2011). In Paluck (2011), the author tests a peer trainer model to affect attitudes around prejudice. The ultimate goal is to understand how far these changed attitudes can spread. Using an Anti-Defamation League anti-prejudice program, peer trainers in U.S. high schools were trained to spot and intervene in instances of prejudice within the school (Paluck, 2011). Peer trainers were selected by the Anti-Defamation League and teachers (following the Valente et al. (2009) model, teachers knowledge of the environment allowed them to select appropriate peer leaders) and schools were randomized to start the program in the fall or spring (Paluck, 2011).

Linear modeling indicated adolescents were more likely to nominate peer trainers as those who would stand up to prejudice and, importantly, there were spillover effects to non-peer trainers when comparing the treatment and control groups (Paluck, 2011). While
behavior change diffused across the network, there were few changes with respect towards attitudes about prejudice and harassment, potentially indicating a different pathway towards influence, or a change that requires more time or more sustained intervention.

While many authors have used the Add Health data to investigate peer effects on education (Calvó-Armengol et al., 2009; Mihaly, 2009; Patacchini and Zenou, 2011; Haynie, 2001), none used an ERGM to understand dyad-dependent structural effects and homophily within the network. In Goodreau et al. (2009), authors estimated ERGMs for 59 Add Health schools. They investigated three cognitive properties: sociality on grade, race, and gender; selective mixing on grade, race, and gender; and propensities toward triadic closure (Goodreau et al., 2009).

Sociality indicates the propensity for a person with a particular characteristic to mix with others. For example, Goodreau et al. (2009) found that older adolescents were more like to be social (send ties) than younger adolescents (where age was proxied by grade), while African-Americans were slightly less social than other races. Selective mixing is synonymous with homophily. Authors found strong grade and gender homophily effects, but not race (Goodreau et al., 2009). However, African-Americans were more likely to be in race homophilous dyads than adolescents from other races (Goodreau et al., 2009). Finally, the authors found consistent evidence of triadic closure across schools, indicating adolescents tended to become friends with their friends’ friends (Goodreau et al., 2009).

By looking at dyad-dependent phenomena, Goodreau et al. identified important social constructs unexplored in dyadic-independent analyses. For example, while African-Americans were more homophilous in their relationships, authors demonstrated this was an effect dependent on the racial makeup of the school. When schools were roughly equal in terms of white/African-American mix, then assortivity was roughly equal between the races. However, when one race was between 10 to 50 percent of the student body, then African-Americans were more assortive, though when either white or African-American students were a small minority within a school, assortivity for African-Americans stayed the same, but was much higher for whites (Goodreau et al., 2009). Assortivity amongst African-Americans tended to be higher in general, but was relatively stable across school
racial makeup; white students demonstrated greater variability, depending on the school racial makeup. In dyad-independent analyses, this factor may otherwise be ignored when determining predictors of behavioral outcomes.

Utilizing the same data as Cappella et al. (2012) and Neal and Cappella (2012), Cappella and Neal (2012) investigated peer victimization within classroom networks. Authors hypothesized structure and composition of classrooms would decrease social isolation amongst children that were victimized by their peers. Using a multi-level model, they identified a significant effect of victimization on centrality; specifically, higher levels of victimization led to lower centrality in the network (Cappella and Neal, 2012). They identified how the victimization/centrality interaction was moderated by classroom-level effects such as class size, grade, proportion of females, prosocial norms, aggression norms, and teacher emotional support. They found smaller classes and a greater proportion of female students lessened the effect of victimization on centrality, while being in a classroom where the teacher provided greater emotional support lessened the effect of victimization on centrality (Cappella and Neal, 2012).

Being able to identify the interaction between structure and composition is important in understanding how to intervene on behaviors. Knowing smaller classes can mediate the effects of victimization within a class setting allows teachers or others to better engage and impact all children in the class. Moreover, teachers setting norms such as emotional support may allow for better rapport between all students, and in ways similar to Paluck (2011), allow for the positive diffusion of norms through the network.

While research on race in networks has found increasing heterogeneity within the network leads to increased racial homophily in relations (Moody, 2001; Lubbers, 2003), in Flache and Stark (2009), authors were interested in understanding the mechanisms by which racially-homophilous relations arise. To better understand the processes behind racial homophily in networks, authors simulated networks where school composition changed, but preference for racial homophily remained equal; this controlled for issues such as being part of a very small minority in a network and replacing the preference for racial homophily with a preference for any type of relation (Flache and Stark, 2009).
Simulating networks longitudinally, Flache and Stark (2009) found that as networks were more heterogeneous, there were consistently rising levels of homophily in race relations, even controlling for the underlying homophily propensity. Therefore, even when controlling for underlying tendencies, it was difficult to interpret how school composition drives racial homophily in a network.

Flache and Stark’s work indicated how and why individuals chose their relations was complex. In small racial minority schools, the tendency towards cross-race ties was a function of having any over no ties; but within a more heterogeneous school, there was a larger ability to discriminate in one’s ties and thereby affect overall network structure. These individual level decisions were mediated by others’ decisions and behaviors in the network.

In network data like Add Health or the data used in this dissertation, directionality of nominations is important. One person may say another person is their friend and that may be reciprocated, though it need not be. Using the Add Health data, Ball and Newman (2013) used information on the direction of nominations to better understand with whom individuals were friends. They found in reciprocated friendships, both individuals in the dyad tended to be of the same rank – that is, they inhabited the same position within the social hierarchy – and even in unreciprocated friendships, there was a good chance that the two individuals were of the same rank (Ball and Newman, 2013). However, in unreciprocated friendships, when individuals were not of the same rank, then it was almost always the lower ranked individual that made the friendship nomination to the higher ranked individual (Ball and Newman, 2013). In addition, while sex and race were not correlated with rank, age was in these networks. The older one was, the higher ranked they generally were in the network (Ball and Newman, 2013). Ultimately, Ball and Newman’s work on rank relation in friendship nominations indicates friends, especially if reciprocated, tend to befriend those of the same social position. Moreover, even in adolescence, social rank is a strong determinant of social behavior. Most interestingly though, even without knowing one’s absolute rank, one can identify those of a similar social hierarchy.
In Haynie and Osgood (2005), authors provided evidence against two widely held beliefs in the literature on peer relations and delinquency. First, the effect of peer relations on delinquency has been overstated in the past; Haynie and Osgood (2005) found with proper controls and peer, not respondent, reports of delinquency, the effect of a percent increase in peer delinquency was a six to 15 percentage point increase in one’s own delinquency. Second, authors found overestimation of peer influence on delinquency was at the expense of other covariates, such as age or attachment to parents (Haynie and Osgood, 2005). Moreover, they found evidence for two mutually accommodating theories: socialization (more delinquent friends leads to higher delinquency by the respondent) and opportunity (more unstructured free time leads to greater delinquency, even if surrounded by non-delinquent friends) that evidence multiple, complex processes happening around peer influence on delinquency (Haynie and Osgood, 2005). In this case, adolescents’ behavior was affected not only by peer behavior, but by time spent with the peers to begin with, which suggests an important role for socialization on behavioral outcomes.

The social ecological model utilizes multiple sources of influence to predict behavioral outcomes. Lubbers et al. (2006) investigated how family, school class, gender, and peer relations predicted peer acceptance in Dutch junior high schools within a social ecological framework. Adolescents were asked to nominate three peers in their class they liked; the in-degree (number of nominations received) for each child was then calculated and standardized within class; since few nominations were made across gender, boys and girls degree scores were created separately (Lubbers et al., 2006). Predicting peer acceptance were individual-level variables, such as perception of athletic competence and extroversion, family-level variables, such as parental education and number of siblings in school, and peer relation variables, such the percentage of classmates who attended the same primary school as the respondent (Lubbers et al., 2006). Girls and boys were analyzed separately.

Using a multilevel model, Lubbers et al. (2006) found perception of athletic competence, extroversion, and a greater percentage of children from the same primary school predicted greater peer acceptance for both boys and girls; additionally, being an ethnic minority was negatively related to peer acceptance for boys, while agreeableness was pos-
itively related to peer acceptance in girls. For both boys and girls, extroversion was most strongly predictive of peer acceptance; moreover, family background was not linked to peer acceptance through any of the covariates. For both boys and girls, Lubbers et al. (2006) demonstrated individual and peer relational information was quite predictive of behavioral outcomes; in this case, social acceptance of peers in school.

While most network research focuses on positive affiliation ties, Berger and Dijkstra (2013) investigated dislike relations among children in multiple schools in Santiago, Chile. Their goal was to better understand popularity and its effects on antipathy nominations. They found children who were more popular were more likely to dislike less popular kids than kids of similar popularity of themselves (Berger and Dijkstra, 2013), reminiscent of Ball and Newman (2013) findings on social hierarchy. The result held as children rose in popularity. To estimate these effects, authors used a SAOM over a one-year period. Structurally, they found few network ties overall, but with significant reciprocity (Berger and Dijkstra, 2013). Moreover, they found that children who were highly disliked at wave 1 were more likely to receive additional antipathy nominations at wave 2 (Berger and Dijkstra, 2013). Computationally though, they found popular children received fewer antipathy nominations and friends tended to agree on who were disliked individuals (Berger and Dijkstra, 2013) by entraining the antipathy network with a separate friendship nominations network (cf. Lusher and Robins, 2013). Interestingly, they did not find evidence of competition amongst popular children to direct antipathy towards one another; instead, it seemed popular children insulated themselves from less popular children and maintained their status through exclusion.

A shortcoming of statistical network analysis on cross-sectional data is the inability to identify separate selection and influence effects. Selection effects arise when one selects relationships with others exhibiting similar behavior, while influence effects indicate changes in a respondent’s behavior due to their peers’ behaviors. In Molano et al. (2013), authors investigated aggressive and prosocial selection and influence effects among classroom networks of fourth grade students in New York City public schools. They hypothesized children with aggressive tendencies, or conversely, prosocial tendencies, may be attracted
to similar students or adapt their behavior to conform with their peers’ tendencies, similar to Corsaro and Eder (1990).

They found no selection effects, though transitive closure, gender homophily, and a propensity for girls to send fewer nominations to others were present (Molano et al., 2013). They did find influence effects for aggression – children were more likely to change their aggression behavior based on peers’ behavior, though the effect was smaller for girls (Molano et al., 2013). Moreover, for children who *a priori* exhibited strong aggression tendencies, there was a significant interaction with peers’ aggression, multiplying the influence effects for these children (Molano et al., 2013). There were no significant influence effects for prosocial behavior.

Molano et al. (2013) demonstrated how children not only conform to others within their social network, but how the network as a whole could influence individuals behavior. In Molano et al. (2013), emphasis was on aggression and prosocial behaviors; however, applications to academics – such as enrollment/attendance in school or achievement – are also behaviors where peer actions could influence an individual.

Similar to Molano et al. (2013), Logis et al. (2013) investigated the interaction of aggressive and prosocial behaviors on popularity. Unlike Molano et al. (2013) who sought to understand the dynamics between aggression and prosociality, Logis et al. (2013) investigated how popularity moderated these behaviors. Using classroom data on fifth graders from the United States’ midwest, they found similar structural effects to Molano et al. (2013); namely, reciprocity in ties, transitive closure, as well as balance, or the propensity to have the same number of outgoing ties as incoming ties (Logis et al., 2013). However, Logis et al. (2013) found girls sent more ties, and received fewer than boys, which differed from Molano et al. (2013). In Molano et al. (2013), there was significant selection homophily in terms of prosociality and popularity, while aggressive children sent more nominations, aggressive children received fewer nominations, and popular children received more nominations (Logis et al., 2013). Finally, confirming their hypothesis that aggressive children would seek ties with prosocial youth for support while maintaining their popularity, they found that the interaction of one’s own aggression with prosociality
by peers and popularity homophily to be significant (Logis et al., 2013).

In terms of influence, Logis et al. (2013) found children assimilated to the network norms around aggressivity, prosociality, and popularity, and there were distinct preference effects for prosociality and popularity (Logis et al., 2013). These results were somewhat different from Molano et al. (2013), who did not find prosociality influence effects. Together, these two studies demonstrate a range of selection and influence effects on individuals’ behavior through the network. Moreover, Logis et al. (2013) demonstrated popularity can be a strong mediator between aggressive and prosocial behaviors of children.

Peer influence extends more generally to peer risk. Rambaran et al. (2013) investigated the impact risk norm salience had on selection and influence effects among junior high students in the Netherlands. They stated that the heterogeneity of previous results may be due to the aggregation of differing status norms within the networks (Rambaran et al., 2013). So, Rambaran et al. separated 47 classes into neutral, slightly positive, and significantly positive risk attitude classrooms. Then, jointly and separately, they estimated SAOMs to understand selection and influence effects adolescents displayed with respect to risk. They found standard structural effects – reciprocity and transitive closure – and some compositional selection effects, like gender homophily and a propensity for boys to send more, but receive fewer, ties (Rambaran et al., 2013). Their main finding was within influence processes. They found adolescents were susceptible to peer risk, with the effect especially pronounced for the more risk salient groups (Rambaran et al., 2013). They concluded this was evidence of status-based influence; that is, the initial environmental position one finds themselves in was an important determinant of how peer norms affected behavior. For a more risk-taking adolescent, being in a high risk salient classroom exacerbated tendencies, which otherwise were checked in low-risk salient classrooms.

Expanding on group-level norms around individual behavior, Ojanen et al. (2013) examined two types of social goals of middle schools students in Finland – communal and agentic goals. Communal goals addressed prosocial and community-oriented aspects of goal seeking, like peer acceptance, whereas agentic goals were more ego-oriented, such as
seeking popularity or relating to high self-esteem (Ojanen et al., 2013). Authors posited communal goals would exhibit selection and influence effects, whereas agentic goals would lead to friendship deselection over time (Ojanen et al., 2013). While Ojanen et al. found evidence of influence among adolescents for both communal and agentic goals, they did not find selection effects on communal goals. However, there was limited evidence of friendship deselection amongst youth with agentic goals (Ojanen et al., 2013). These findings indicate, like Rambaran et al. (2013) and Logis et al. (2013), influence is not solely limited to behaviors, but also agency and communication, suggesting multiple intervention points in the cognitive behavior of adolescents.

In novel work looking at economic ties within households, Potter and Handcock (2010) fit ERGMs to a Malawian village and found network structure, as well as relationships, helped describe resource flow within families. Due to the HIV epidemic in sub-Saharan Africa and traditional kin-based systems of support, Potter and Handcock (2010) were interested in understanding dynamics of resource exchange within households in light of the HIV epidemic. They found intra-household resource transfer was likely from parents to children, between married couples, and between regular dwelling members of the compound, while transfer was less likely to working age adults. Moreover, transfer was most likely between males and least likely from females-to-males (Potter and Handcock, 2010). Finally, while there was evidence of hierarchy within resource networks, there was evidence that generalized exchange pervaded resource transfers within the village; potentially owing the similar economic opportunity of everyone in the village, there was indication that all were as likely to receive transfers as opposed to a certain few (Potter and Handcock, 2010).

Extending work on popularity and choice in networks, Belot and van de Ven (2011) investigated favoritism in the context of a controlled experiment with children. Often, favoritism is hypothesized to – in an economic sense – decrease economic efficiency. However, as Belot and van de Ven (2011) demonstrated, that may not always be the case. Using groups in a two-round competitive game, where the friendship ties amongst group members were known, Belot and van de Ven found that if a friend was selected to compete
in the second round by the group leader, then the friend performed better relative to their first round performance. In fact, if the friend was not a top performer in round one, their performance in round two was indistinguishable from the performance of top performers in round two (Belot and van de Ven, 2011). The authors concluded that while favoritism may on its face reduce efficiency, there may be good reason to think that friendship can mediate favoritism in unexpected ways. Friends may be more willing to provide extra effort and improve performance given selection, certainly fitting with how friendship or other types of affiliative relations can influence individuals efforts, behaviors, or actions.

To identify specific pathways adolescents used to create friendships, Schaefer et al. (2011) investigated the role extracurricular activities – like sports, arts, and school clubs – had on the propensity to form ties between children. Using the Add Health data, authors found that extracurricular activities did assist in forming ties, with adolescents showing strong homophilous tendencies overall (Schaefer et al., 2011). However, the effect was even more pronounced for those in high school compared to middle school, which the authors describe as somewhat expected, given older adolescents greater autonomy, expanded choices for extra-curricular activities, and generally a larger setting, which induced adolescents to find a “home” where they could develop key relationships (Schaefer et al., 2011).

Most interesting though was their longitudinal work on tie formation. Using a second wave of data collected eight months after the first, they found having a friendship at time 1 was a significant predictor of friendship at time 2 (Schaefer et al., 2011). In the two schools they studied, one school exhibited effects consistent with new tie formation, while the other exhibited tie maintenance, but not tie formation (Schaefer et al., 2011). These effects indicated unique processes happening within the school and spoke to the environment’s ability to influence the structure of friendship formation.

Often, when considering ties between people in social space, geographic space is ignored. However, there is good reason to believe that both social and geographic space are correlated (McPherson et al., 2001). By being geographically close to someone else, there is increased chance for interaction, and consequently, tie formation. In Preciado
et al. (2012), authors investigated the role geographic proximity had on tie formation amongst adolescents in an isolated Swedish town, while in Daraganova et al. (2012), authors investigated proximity and ties amongst job seekers in Australia. Preciado et al. (2012) approached the problem in two ways. First, they used a generalized additive model (GAM) to model the dependence of distance between two people on the propensity to form a friendship tie. However, this did not account for the dependency structure of the social relations between respondents, potentially overestimating the effects of distance on tie formation (Preciado et al., 2012).

To remedy, authors employed SAOMs using the relevant features from the GAM to specifically distance effects (Preciado et al., 2012). They found evidence of a negative relationship between distance and tie formation, evidenced through both the GAM and the SAOM; as distance increased, the likelihood of tie formation decreased (Preciado et al., 2012). However, since adolescents attended school for the majority of a given day, they interacted distance with school attendance and found the effect of distance was moderated by same school attendance (Preciado et al., 2012). Ultimately, Preciado et al. (2012)’s work highlighted the importance of distance as a predictor of tie formation/maintenance and illustrated ways in which general patterns of distance and tie formation could be deduced prior to using a statistical network model.

In Daraganova et al. (2012), authors used multiple distance interaction functions defined in Butts (2002) to test the effect of distance on network tie formation in ERGMs. They found ties were more likely between people who were spatially close, but spatial distance was unrelated to network clustering (Daraganova et al., 2012). They concluded spatial information may assist in understanding initial tie formation, but it was not a requirement to understand the nature of the network effects (Daraganova et al., 2012). Spatial information can help explain network tie formation (Preciado et al., 2012; Daraganova et al., 2012), specifically at proxamite distances. However, geography’s further contribution to network formation is likely context-specific.

While the concept of behavior contagion has been well-studied (cf. Christakis and Fowler, 2007, 2011) and debated (Cohen-Cole and Fletcher, 2008), neither study nor crit-
icism employed more advanced statistical network techniques to model behavior contagion in a network. In Kiuru et al. (2012), authors investigated the contagion and convergence of depression between peer adolescents in Finland, while de la Haye et al. (2011) looked at obesity contagion among adolescents in Australia. According to Kiuru et al. (2012), contagion represented an increase in behavior to resemble a peer, while convergence represented a “meeting in the middle” amongst peers on a behavior; that is, a less depressed adolescent may become more depressed similar to their peer, or a more depressed adolescent may become less depressed similar to their peer. Using SAOMs, Kiuru et al. (2012) found evidence of convergence, but not contagion, controlling for network structural and compositional effects. This indicates different approaches to address behavioral influence in a network. With contagion, there is an emphasis on stopping behavior transmission; but with convergence, one can adjust behaviors to influence the network towards a certain outcome; in this case, less depression.

In Australia, de la Haye et al. (2011) also found little evidence for contagion of obesity, though they found significant selection effects with the SAOMs. Specifically, non-obese children were less likely to nominate an obese child as a friend, though the opposite relationship did not hold; moreover, there were significant homophily effects around obesity (de la Haye et al., 2011). As opposed to Christakis and Fowler (2007), de la Haye et al. (2011) did not find evidence of obesity contagion using a model that can separate both selection and influence effects.

Homophily, or the tendency to be connected to those similar – as opposed to those dissimilar – to oneself, has strong roots in social network analysis. From early studies in the 1920s and 1930s (Wellman, 1926; Parten, 1933) to current-day studies (de la Haye et al., 2011; Rambaran et al., 2013), homophily has played a consistent role in explaining network formation. McPherson et al. (2001) reviewed the literature on homophily and discussed various ways in which homophily was present across status and value attributes. For race, gender, age, religion, occupation, education, social class, behaviors, beliefs, and geography, homophily has shown both an important effect in creating – and dissolving – ties within networks (McPherson et al., 2001).
Though much of the work on cognitive factors, like homophily, selection, and influence effects, deals with individuals, there are analogous effects working at different levels. In Grannis (2009), the author explored how neighborhoods affect the social networks of its inhabitants. His research – spurred by an early encounter in a neighborhood with a growing gang problem – revolved around the built environment and the impact on its inhabitants. Communities grew through a series of phases – from having opportunity to interact, to having casual, non-committal contact, to growing relationships, and finally, establishing ties (Grannis, 2009). As Grannis discussed, the sequential order of effects was important. At each stage, there were opportunities to transmit various network correlates, like homophily/selection (in terms of where one settles) and influence (setting common norms within the neighborhood; for example, looking out for others’ children) that can define a neighborhood (Grannis, 2009).

Grannis’s work has distinct tie-ins with the work of Daraganova et al. (2012) and Preciado et al. (2012) in terms of geography, the bounding of neighborhoods, while relating to the work of Haynie (2001), Lubbers et al. (2010), and Cappella et al. (2012) regarding network structural effects. Networks are not solely person-based – they can be driven structurally and cognitively by the neighborhood characteristics in which they are situated.

2.2.4 Harnessing the Power of Network Information for Change

While change is often conceptualized at the individual level, “…social network analysis turns these notions on their head” (Valente et al., 2004, p. 1702), since network interventions can produce change: social, behavior, process efficiency, and new technology adaptation (Valente, 2012). Unlike individual-level change though, a network intervention is dynamic, since it involves at least a dyad of participants, if not more. A change to one actor introduces a potential cascading effect to all other actors in the network. In a review of network intervention types, Valente (2012) provided four basic typologies of network interventions: identification, segmentation, induction, and alteration.

An identification strategy focuses in on key individuals – defined in a variety of ways – to execute an intervention. Utilizing a highly central peer leader to affect change is one
example (Paluck, 2011; Paluck and Shepherd, 2012). Segmentation, however, eschews the individual for the group; so, an intervention works through a particular sub-group of the network. In Valente et al. (2003), peer-nominated groups led to lower intentions of smoking compared to groups that were randomly assigned. By developing purposeful groups of participants, the intervention was able to harness sub-network effects to increase the efficacy of the program. An induction strategy can be useful in harnessing people into the network intervention. Valente (2012) was an example using respondent-driven sampling. By finding “seeds” within an unknown or hard-to-reach network, one can identify the underlying structure of the network through adaptive link-tracing. Often, for hidden or underground networks, the use of word-of-mouth campaigns, similar to respondent-driven sampling, is the only way to develop the base network for experimentation. Finally, alteration involves the changing of respondents or links between respondents, to suite the purposes of the intervention (Valente, 2012). This takes many forms – it may involve innoculating medical staff to act as a transmission barrier to disease spread or adding a clean-water well to a village’s water distribution system. In any case, with alteration, the focus of the intervention is squarely on system dynamics (Valente, 2012).

The choice of network intervention strategies revolve around the intent for the intervention. If the intervention in question is one of norms or culture, then the use of network ties predicated upon trust, interpersonal understanding, and reciprocity are likely key (Valente, 2012), as in Cappella and Neal (2012). However, if the intervention centers on knowledge exchange or technical transfer, as in Conley and Udry (2010), then utilizing networks ties exhibiting experts with credible knowledge are key (Valente, 2012). In Valente et al. (2003), authors were interested in evaluating peer-led tobacco prevention programs within schools. They evaluated three network-based designs – first was to assign children at random to peer groups, the second assigned children to peer groups based on teacher recommendations, and the third used friendship-based nominations to peer leaders; in both the first and third treatments, children’s friendship nominations identified peer leaders (Valente et al., 2003). Authors found greater appeal for leaders/groups in the peer network group, compared to random assignment, as well as a lower intention
to start smoking (Valente et al., 2003). Authors concluded that using both a network-based intervention (peer-led training), but using the network nominations to create the study groups, was an effective way to boost impact of a tobacco prevention intervention in schools (Valente et al., 2003).

While the use of RCTs has proliferated in recent years (cf. Kremer, 2003; Angelucci et al., 2010; Burde and Linden, 2012, 2013), few have used networks as outcomes. In Farmer et al. (2010), authors investigated how effective was a teacher training to identify middle school peer groups. They reasoned middle school was a time of change in students’ lives as they reshuffle friendships and often social hierarchy; moreover, processes like bullying or ideation around dropping out become more salient at this time (Farmer et al., 2010). By training teachers to identify peer groups and who interacts among whom, there was a reasonable chance teachers might be able to intervene to address behavioral issues like bullying. Farmer et al. (2010)’s RCT – while only involving eight schools – indicated that teachers who received the training were more successful at naming various groups within their school. The authors take this as preliminary evidence that through intervention, one may be able to better assess and impact adolescent social networks.

Ultimately, while the scope for network analysis in intervention research is large, its application thus far has been minimal. In Gest et al. (2011), authors discussed additional ways to integrate network analysis into interventions. They conceptualized two levels of interaction; first, was the network level (Gest et al., 2011; Valente et al., 2004). This would involve acting upon the structure of the network, such as implementing a program to increase the number of ties amongst individuals in the network or creating links between separate sub-groups. Second, were operations at the individual level seeking to influence behavior, selection, or influence within particular individuals in the network (Valente et al., 2004; Valente and Fosados, 2006; Gest et al., 2011). Moreover, any work regarding influence should take cues from mass media, where messaging must be both personal and entertaining (Valente and Fosados, 2006). Mass media efforts, when focused on behavior change, often seek to influence knowledge, attitudes and/or practice; working through a network-based intervention could increase message strength and efficacy, while multiplying
the number of change agents (Valente and Fosados, 2006).

While work to identify key leaders (via centrality measures) have predominated (cf. Paluck, 2011; Paluck and Shepherd, 2012; Valente et al., 2003), techniques such as SAOMs to identify selection and influence effects could be extended. For example, in many of the SAOMs cited, authors only identified effects, but did not discuss how that information could be used to induce a particular change. Moreover, the use of network analysis is not limited to interventions; it can be used in monitoring and evaluation as well, providing information on who in the network adopted change, a person’s role in the network, and how these attributes affect resource allocation in the future (Valente et al., 2004). Working to address both structural and behavioral change, however, should ultimately be a function of both network analysis as well as a transdisciplinary approach to theory, touching on sociological, anthropological, economic, and psychological theory (Gest et al., 2011; Valente et al., 2004).

2.3 Data

Data were collected in the fall of 2007 (September 29, 2007 through November 4, 2007) as part of a randomized control trial (RCT) assessing the impact of a community-based rural schooling project. The project, Partnership for Advancing Community Education – Afghanistan (PACE-A), was funded by the United States Agency for International Development (USAID) from April 2006 through September 2011.\footnote{The evaluation of Catholic Relief Services’ PACE-A operations was not funded by USAID; the evaluation was funded through generous support from the National Science Foundation, the Spencer Foundation, and the Weikart Family Foundation.} PACE-A was implemented by a consortium of non-governmental organizations (NGOs) led by the Cooperative for Assistance and Relief Everywhere (better known as CARE International, or CARE) (USAID, 2011).\footnote{Other organizations in the consortium included the Aga Khan Foundation (AKF), Catholic Relief Services (CRS), and the International Rescue Committee (IRC).} The purpose of PACE-A was to extend educational reach throughout Afghanistan by establishing community-based schools in areas otherwise unserved by the Afghan public education system. Practically, this meant schools were established in remote, rural villages. PACE-A operated in 17 of 34 Afghan provinces (Burde, 2010).
The RCT evaluated CRS’ implementation of PACE-A in Ghor province of central Afghanistan. Treatment villages were those villages where a community-based school (CBS) was established in the summer of 2007; control villages were slated for a CBS in the spring/summer of 2008. See figure 2.2 for a map of Afghanistan within the surrounding Central/South Asia region. In figure 2.3, one can see the highlighted province – Ghor – in which all surveying took place.

![Figure 2.2. Central/South Asia – Area of Research](image-url)
While data were collected in the spring of 2007 and 2008 as well, network data were only collected only in fall of 2007; these are the only data analyzed here. A team of 17 Afghan surveyors (15 males and two females) were hired and trained for this survey. Each surveyor received three days of training prior to commencing work. Training consisted of general surveying techniques, an introduction to the instruments used, in-depth discussion of each question, practice interviews, and a short training post-test.

Figure 2.3. Provinces of Afghanistan – Survey Area
Most male surveyors worked independently; female surveyors worked in conjunction with a male counterpart, per social norms in rural Afghanistan. Female surveyors conducted interviews with female head-of-households and female children; in addition, female surveyors were able to interview male children.

Figure 2.4 presents the two districts in which CRS’ PACE-A schools were subject to evaluation. Thirty-one villages in Ghor province (15 in Chagcharan district and 16
in Sharak district) participated. These villages are represented as red dots on figure 2.4. As a randomized control trial, 13 villages were assigned to the treatment group and 18 were assigned to the control group. In both treatment and control villages, surveyors visited every household in the village (a census) and were able to interview 93.8 percent of households; 4.2 percent of households were empty at the time of surveying and 2 percent of households were missed for other reasons, such as accessibility. No household refused the survey and there were no systematic differences between treatment and control groups in surveying. In addition, 92.4 percent of boys and girls eligible for the survey were surveyed. Table 2.1 presents data on household surveying by treatment status.

<table>
<thead>
<tr>
<th></th>
<th>Treatment</th>
<th>Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Households</td>
<td>680</td>
<td>667</td>
</tr>
<tr>
<td>Households Surveyed</td>
<td>636</td>
<td>635</td>
</tr>
<tr>
<td>Households Empty</td>
<td>44</td>
<td>32</td>
</tr>
<tr>
<td>Total Girls</td>
<td>401</td>
<td>337</td>
</tr>
<tr>
<td>Girls Surveyed</td>
<td>389</td>
<td>329</td>
</tr>
<tr>
<td>Girls Refused</td>
<td>12</td>
<td>8</td>
</tr>
<tr>
<td>Total Boys</td>
<td>434</td>
<td>402</td>
</tr>
<tr>
<td>Boys Surveyed</td>
<td>389</td>
<td>360</td>
</tr>
<tr>
<td>Boys Refused</td>
<td>45</td>
<td>42</td>
</tr>
</tbody>
</table>

Four types of data were collected: household data, child-level data (from an adult about each child in the household between the ages of 6 and 11), child-level achievement in language and mathematics (from each child in the household between the ages of 6 and 11), and network nominations (from each child in the household between the ages of 6 and 11). Each of these data sources are described below; copies of the instruments used are provided in Appendix B.

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*In 2005, Afghanistan re-districted portions of Chagcharan district in Ghor province. The spatial data used to create the maps in figure 2.4 relies on the pre-2005 re-districting and therefore a village that is now considered part of Chagcharan appears in Sharak district.*
2.3.1 Survey Procedure

The survey team worked in two groups, each surveying roughly a village per day. Typically, groups would arrive at the village and ask to speak with village elders. The survey lead would describe the purpose of the survey, with whom the team was affiliated (Columbia University, who was conducting the evaluation; CRS, the program implementing agency), and ask for permission to survey house-to-house. While not strictly necessary, consulting with village elders prior to surveying ensured easier access to the village population.

After receiving permission from village elders (no village refused), surveyors visited a house and asked for the head of household. If the head of household was not available, they asked for “the most responsible person in the household willing to respond to [a] survey.” If the respondent orally consented to the survey, the surveyor began the household survey.

Once the household survey was complete, the surveyor then asked questions of the respondent about each child in the household between the ages of 6 and 11. The surveyor then asked to survey each child enumerated by the respondent.

Children were administered oral assent; if they chose to participate, the child took two short, oral/visual tests – one language (Dari) and one mathematics. The language test consisted of four questions and the mathematics test consisted of five questions. After the tests, each child was asked to name children in the village with whom they were friends and, separately, the children with whom they played. These data comprise the network nominations.

Once all children had been interviewed in the household, the surveyors thanked the household for their participation, placed a chalk mark on the ground in front of the household to signify it had been surveyed, recorded the geolocation of the household with a handheld geographical positioning system (GPS) device, and went to the next unsurveyed house. Once all households in the village had been surveyed, the survey team thanked the village elders for their cooperation and departed.

2.3.2 Household Survey

The household survey began with the respondent stating who was the head of the household; if the respondent was not the head of the household, then the respondent stated
their relationship to the head of household. The respondent was asked to estimate, in years, how long the family had lived in the village and how they described the household. Because ethnicity is not a universally-recognized mode of describing a household in parts of Afghanistan, respondents were allowed to describe their household in terms of ethnicity (e.g., Pashtun, Tajik, Hazara) as well as more generally (e.g., Dari-speaking, Afghan); an option to describe the household in “other” terms was also available.

The respondent then described how the household primarily made its living by describing the household’s main wage earner’s occupation, education, and age. Next, the respondent was asked to describe the size of the household, how often the household ate meat, how much irrigated land (in jeribs\(^9\)) the household had under cultivation, and how many sheeps and goats the household owned. Questions about eating meat, irrigated land, and number of livestock were proxies for socio-economic status; more wealthy households ate meat more regularly and had more irrigated land and livestock.

Next, the respondent answered a series of questions about their opinions on children’s education, including what a child’s future would be like with an education as compared to a future without an education, what should a child learn in school, and up to what age should a child go to school. These questions were asked separately for girls and boys, since parental educational aspirations may differ based on the child’s gender (Aturupane et al., 2013).

The respondent was then asked about a child’s punishment if they misbehaved at home and at school. Answers ranged from speaking with the child about the inappropriate action to employing corporal punishment. These were proxy measures to indicate the level of violence the household was willing to entertain with respect to children.

Finally, to get a sense of the household’s belief in various civic institutions, the respondent was asked whether they “trusted” the central government of Afghanistan, the provincial government of Ghor, international non-governmental organizations (NGOs), and neighbors in their village. In addition, they were asked whether those same institutions played an important role in the education of their children.

\(^9\)One jerib is equal to 2,000 m\(^2\).
2.3.3 Child Survey

After completing the household survey, the same respondent was asked to answer questions about all children in the household between the ages of 6 and 11. The respondent was asked how, for each child, the child was related to the head of the household, the age of the child, the gender of the child, how many years of schooling the child had attended, and the chores the child did around the household (and if the child was paid for any of those chores).

In addition, because children lived with relatives or others for schooling opportunities in Afghanistan, a series of control questions were asked to ascertain whether the child lived in the village in the spring of 2007 (prior to the inception of the CBSs), and if not, at what point did the child arrive in the village.

If the respondent indicated that the child had attended school before, the respondent was asked what type of school the child attended (e.g., government/public school, mosque school, madrassa, an international NGO school, or something else). Finally, the respondent was asked whether the child attended school on the last day school was in session, approximately how often the child attended school, and where the school was located – inside the village or outside the village (child traveled back-and-forth; child stayed at school).

2.3.4 Child Achievement Tests

After concluding the interview with the household respondent, the surveyor asked each child discussed in the child survey to take short language and mathematics tests. Each of the questions for language and mathematics consisted of three examples of the question. All questions were selected from Afghan government curricula for what children in the first year of formal education should learn.

After assenting to the test, each child (individually) was asked four language questions.

---

10 A mosque school is akin to what one might consider “Sunday school” in the Christian faith; a place where children learn basic reading skills through lessons on their faith.

11 A madrassa is generally a boarding school away from where the child lives that will help serve as the basis of a religious education.

12 Most village-based schools ran six days a week (break on Friday), but only operated between two and four hours a day, usually in the morning. Government/public schools may have operated differently.
in Dari and five mathematics questions. The language questions consisted of two questions identifying letters in the Dari alphabet (one with “easy” letters and one with “hard” letters) and two questions reading words (again, “easy” words and “hard” words).

The mathematics questions consisted of one question identifying numbers (Arabic numerals), one question counting items in a picture, one question identifying the greater number in a series of two numerals, one question adding numbers, and one question subtracting numbers.

For each question described above, three examples were shown. Surveyors marked children’s responses based on the number of examples answered correctly. Therefore, a child’s score on any particular question (language or mathematics) could range from 0 to 3.

### 2.3.5 Friendship/Playmate Nominations

After completing the achievement tests, children were asked to nominate two sets of children that comprised their social networks. First, they were asked to list children they were friends with in the village. Second, they were asked to list children they played with in the village. Children were not limited in the number of nominations they could make, nor were they limited to an age range for the children they named. They could not, however, self-nominate themselves as a friend or playmate. They were then asked, for each nomination, if the person named was a sibling. To facilitate matching, children were also asked for the friend/playmate’s father’s name.

### 2.3.6 Data Handling

In total, the household survey was 35 questions long and took approximately 35 to 45 minutes to complete. Respondents were asked questions by the surveyor in Dari and surveyors recorded responses on individual answers sheets per household. For the child survey, the respondent answered 16 questions per child between the ages of 6 and 11 in the household. On average, the child survey took between 5 and 10 minutes per child. The child achievement test was nine questions long with three examples per question. Per child, this took on average 5 to 20 minutes. The children’s friendship nominations
consisted of six questions and took on average 5 to 10 minutes per child.

For nomination data, surveyors matched the nominated child’s name and father’s name with household and child data from elsewhere in the village. Because children were not restricted to naming children between the ages of 6 and 11, there were children nominated on which surveyors had no information. These children were coded and retained for network calculations, but maintained no links to children in the household/child datasets.

All data were sent in paper form to a trained data entry operator in India who double-entered data into a spreadsheet. Any errors between the two entries were resolved manually with the original data or flagged for follow-up with the research team. Data were then sent in Microsoft Excel spreadsheets for further cleaning and analysis to the research team in New York, New York. Any unresolved issues from data entry were reconciled between the data cleaning team in New York and the surveyor manager in Afghanistan.

Data cleaning for the household, child, and achievement portions of the survey happened in New York from January 2008 through September 2008. Nominations data were cleaned from June 2011 through August 2011 in Santa Monica, California.

During the first round of data cleaning, proper matching and identification of households and children for the household, child, and achievement were of primary importance. In addition, logical inconsistencies (e.g., “number of children in household” equals zero, but child data were present for two children) and basic descriptive statistics were produced. During the second round of data cleaning, nomination identification numbers were checked for matches with the household and child data. In addition, network measures, such as density, in-degree, out-degree, degree and betweenness centralization, components, dyads, and isolates were calculated at the respective (network or node) level. These nomination data were then merged with household, child, and achievement data to form the dataset for analysis in this dissertation.
Chapter 3

Methods

The conceptual model (figure 2.1) postulated in Chapter 2 relates a behavioral decision to a person’s social cognition, the structure of the network they are situated within, and the broader environment that surrounds them. Interaction with others, along with personal characteristics, influence how and what one does. This has been termed social influence (Robins et al., 2001) and with a network typology, one can determine which environmental, structural, and cognitive parameters are influential in determining a particular behavioral decision.

Using the $p^*$ model as a base, Robins et al. (2001) built the social influence network model from various components – collective effects, social position effects, and network effects. Collective effects encapsulated effects separate from the tie-based nature of the current network. For example, attitudes about race do not depend upon the school network in which a child is enmeshed, but are more likely transmitted through passive experience elsewhere. So, a child’s view towards race is important in understanding the nature of the network, but is independent of the network itself. Social position effects represented the actions taken by the individual within the network, regardless of what others in the network did (Robins et al., 2001). For example, whether a network shows a tendency towards triadic closure is dependent upon all ties in the network; however, each individual within the network first makes their position known through the ties they send (or do not send) to others within the network.

Finally, network effects include dyad-dependent actions; in other words, the structure
of the network is dependent not only on individual actions, but upon mutual actions, i.e. how my actions induce others’ actions. These are akin to reciprocity or transitivity, or popularity and activity spreads (Robins et al., 2001). While ERGMs have replaced the $p^*$ models over time, the same process described by Robins et al. (2001) with respect to the social influence model are applicable. Social influence can be estimated in an ERGM; however, given the cross-sectional nature of data in an ERGM, there is no differentiation between selection (choosing friends based on an attribute) and influence (adopting the behavior of a friend).

While “most standard statistical approaches such as logistic regression require independence... whereas for networks we generally expect dependence of some sort....,” (Koskinen and Daraganova, 2013, p. 52) a $p^*/$ERGM is specified to model social influence allowing for interdependence between individuals in the network. Because of the interdependence assumptions that ERGMs model, one can determine both individuals’ characteristics on the propensity to form ties and the structural tendencies that underlie tie formation. Structural tendencies – or the propensity to form ties – are impossible to model using regression analyses because of the tie-, not actor-based, level of analysis. Moreover, where there are interdependencies between actors, regression will mismeasure individual attributes, given regression’s assumption of independence.

However, I argue that using ERGMs to understand network structure and dyad-dependent attributes can provide information that can be related back to individual-level outcomes, like math and language performance. By adapting the results of ERGM specifications, I propose to use this network information as covariates within a multi-level model (MLM) relating village-, household-, and child-level effects to child-level outcomes.

In this chapter, I start by reviewing ERGMs in detail, including the parameters used in analyses, their interpretation in the context of relational data, model diagnostics, and goodness-of-fit statistics. Next, I discuss the use and specification of MLMs. I conclude with ERGM and MLM specifications to estimate math and language performance of children in Afghanistan.
3.1 Exponential Random Graph Models

Social network analysis (SNA) is primarily concerned with understanding the relationships between individuals (Wasserman and Faust, 1994). These relationships can be represented in a variety of ways – it could be co-membership in a club, friendship, marriage, or kinship. In fact, ties do not need to be positive relations; one could model a network of antipathy between people (Berger and Dijkstra, 2013). Regardless of the relationship type, networks are formed by representing individuals as nodes and the relations between nodes as edges.

However, traditional analysis – such as linear/non-linear regression – of networks has encountered two problems in particular. First, actors in network data are interdependent upon one another and therefore, observations are not independent, a fundamental assumption of regression techniques. Second, network structure – such as triadic closure and generalized exchange – are difficult to model with traditional methods due to dyad-dependence. Therefore, network analysis has traditionally relied on descriptive analyses – counts of network structures, like the triad census (Holland and Leinhardt, 1970), or degree distributions and the discussion of core/periphery structure (Borgatti and Everett, 1999). Moreover, network visualization had played an important role in understanding both structure and substance of networks (cf. Granovetter, 1973; Padgett and Ansell, 1993).

However, the use of statistical techniques with network data is not new. The Erdös-Rényi/Bernoulli graph is equivalent to an ERGM that just models ties in the network (Erdös and Rényi, 1959; Frank, 1981). These random graphs fail to capture much of the network structure beyond simple tie formation. The $p1$ model of Holland and Leinhardt (1981) was a dyad-independent model, which stepped beyond tie formation to incorporate dyad-level information. However, dyads were treated independent of one another, meaning dyad-level information, like gender homophily, could be modeled, but higher-order network effects – where the actions of another were dependent on another – were still not possible. In 1986 though, Frank and Strauss (1986) introduced Markov graphs that, for the first time, allowed for conditional dependence between observations; that is, two actors were assumed to be conditionally dependent upon each other if they shared a tie with a common
third actor. This formed the basis for ERGM work in the future. By the mid-1990’s, Wasserman and Pattison (1996) identified the \( p^* \) model that used a pseudo-maximum likelihood function to estimate model parameters. However, the properties of the pseudo-maximum likelihood estimator were unknown, providing potentially misleading results (Snijders, 2002; Snijders et al., 2006; Robins et al., 2007a,b).

Advances in the form of Monte Carlo estimation of the maximum likelihood using simulation (Snijders, 2002; Snijders et al., 2006; Robins et al., 2007a,b) and the development of terms that more truly capture the complexity of network ties, such as geometrically-weighted in/out-degree (Hunter, 2007; Goodreau, 2007; Robins et al., 2009), have allowed ERGMs to better model network data. ERGMs incorporated model terms for network structure, personal attributes, dyadic attributes, spatial information, and information on alternative network ties (Lusher and Robins, 2013). The model therefore describes a wide variety of influences on tie formation within a network, while overcoming some of the initial shortcomings of network modeling, such as pseudo-maximum likelihood estimation and Markov dependence assumptions.

### 3.1.1 Mathematical Basis of ERGMs

For \( Y \), a network represented as a \( n \)-by-\( n \) adjacency matrix where

\[
Y_{ij} = \begin{cases} 
1 & \text{for an edge between actors } i \text{ and } j \\
0 & \text{else},
\end{cases}
\]

the probability of a tie for any given realization of \( Y \) can be modeled with an ERGM as

\[
P(Y = y) = \frac{\exp \left\{ \sum_{A=1}^{N} \eta_A g_A(y) \right\}}{\kappa}.
\]

In Equation 3.1, \( g_A(y) \) is a vector of sufficient statistics, indexed by \( A \), with corresponding parameter estimates, \( \eta_A \). The set of sufficient statistics is user-defined, based on the various ERGM parameters available for modeling. The \( \kappa \) terms represents a normalizing constant such that Equation 3.1 sums to a proper probability distribution. The interpretation of any parameter \( \eta_A \) is the conditional log-odds of a tie for a unit increase in \( g_A \).
created by a tie in the network. Estimation is possible for both directed \((y_{ij} \neq y_{ji} \forall i, j)\) and undirected \((y_{ij} = y_{ji})\) networks.

Because of the necessity of the \(\kappa\) term, direct estimation of an ERGM is seldom possible, except for very small or simple networks, given \(\kappa\) represents the sum of \(\eta_{A|A}(y)\) over all possible network configurations (Goodreau, 2007). Therefore, an ERGM estimates the maximum likelihood for the set of statistics modeled in Equation 3.1. When a dyad-independent (i.e., estimation is not conditional upon a third actor) model is estimated, logistic regression can be used. However, with dyad-dependent models, Markov chain Monte Carlo (MCMC) methods are implemented for estimation (Snijders, 2002; Robins et al., 2007b).

Given the intractability of directly estimating dyad-dependent ERGMs because of the number of possible network configurations, an MCMC process uses an initial starting value (i.e., \(y\), a particular realization of network \(Y\)) of the network and sets in motion a Markov process to change ties in a network. That is, where

\[
y_{ij} = \begin{cases} 
1 & \text{for an edge between actors } i \text{ and } j \\
0 & \text{else}
\end{cases}
\]

is the starting specification of \(y_{ij}\) within the network realization \(y\), after a particular step in the Markov process, \(y_{ij}\) becomes

\[
y'_{ij} = \begin{cases} 
1 & \text{if } Y_{ij} \text{ was } 0 \\
0 & \text{if } Y_{ij} \text{ was } 1
\end{cases},
\]

assuming any particular \(y_{ij}\) was affected by the Markov process at a given step. After the execution of a user-specified number of steps, a realization of the Markov process is sampled, \(y'\). The Markov process continues until the user-specified number of samples from the Markov process is complete. Statistics for the resulting Markov process samples are obtained and compared to determine maximum likelihood improvement. The Monte Carlo process repeats until either (a) a convergence test indicates convergence on an approximate maximum likelihood or (b) the maximum number of iterations in the MCMC process is reached. The maximum likelihood estimate can be reached using a variety of
methods, including maximizing the log-likelihood function (Goodreau, 2007) or solving the methods of moments equation for the an exponential family model (Snijders, 2002).

The result of the MCMC process are parameter estimates ($\eta_A$) for the set of statistics modeled ($g_A(y)$) in the ERGM. Being from the exponential family, these parameter estimates represent the conditional log-odds of a tie for a unit increase in $g_A(y)$ (Goodreau, 2007). Coupled with standard errors, ERGM parameter estimates indicate whether the statistic, $g_A(y)$, is more (positive $\eta_A$) or less (negative $\eta_A$) likely than random chance of occurring in the network, given the network realization modeled.

### 3.1.2 Statistics Modeled in ERGMs

A range of statistics, $g_A(y)$, can be modeled within the ERGM framework. Statistics often modeled as part of the social influence model are presented in Tables 3.1 and 3.2 (Robins et al., 2001; Koskinen and Daraganova, 2013). They represent basic structural tendencies within a network as well as compositional effects. While statistics for a directed network are presented, analogous statistics are available for undirected networks.

An ERGM utilizes structural terms to categorize the various tendencies within the network. The most basic ERGM term is edges, which represents a tie from one person to another. It represents basic tendencies towards connectivity within the network. A significantly positive/negative edges term represents more/less ties within the particular network than would be expected by chance.

The mutual term represents reciprocity of ties within the network. That is, if person A nominates person B as a friend, does the person B also nominate person A as a friend? A significantly positive/negative mutual term represents more/less reciprocity within the particular network than would be expected by chance. Reciprocity is important because it values the relation between actors from both perspectives. With an asymmetrical tie, one knows that person A values person B as a friend; however, the reciprocation of friendship by person B to person A is a stronger indicator of friendship. In a model of influence, reciprocity indicates that each person in the dyad can influence the other.

The twopath term represents the connection of three distinct actors in the network (Wasserman and Faust, 1994). Person A sends a tie to person B, who sends a tie to
Table 3.1. Description of Directed Structural Statistics for Exponential Random Graph Models

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Visualization</th>
<th>Formula</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>EDGES</td>
<td>![Edges Visualization]</td>
<td>$\sum_{i,j} y_{ij}$</td>
<td>Sum of all ties in network</td>
</tr>
<tr>
<td>MUTUAL</td>
<td>![Mutual Visualization]</td>
<td>$\sum_{i&lt;j} y_{ij}y_{ji}$</td>
<td>Sum of all reciprocated ties in network</td>
</tr>
<tr>
<td>TWOPATH</td>
<td>![Twopath Visualization]</td>
<td>$\sum_{i\neq j\neq k} y_{ij}y_{jk}$</td>
<td>Sum of all paths containing exactly one in-degree and one out-degree</td>
</tr>
<tr>
<td>GWIDEGREE</td>
<td>![Gwidegree Visualization]</td>
<td>$\sum_{i=0}^{n} e^{-\alpha y_{ii}}$</td>
<td>Indegree distribution, accounting for decrease in marginal utility of each additional nomination received</td>
</tr>
<tr>
<td>GWODEGREE</td>
<td>![Gwodegree Visualization]</td>
<td>$\sum_{i=0}^{n} e^{-\alpha y_{ii}}$</td>
<td>Outdegree distribution, accounting for decrease in marginal utility of each additional nomination sent</td>
</tr>
<tr>
<td>GWESP</td>
<td>![Gwesp Visualization]</td>
<td>$e^{\theta t} \sum_{i=1}^{n-1} \left{ 1 - \left(1 - e^{-\theta t} \right)^{i} \right} \sum_{i\neq j\neq k} y_{ij}y_{jk}y_{ki}$</td>
<td>Transitive triplet distribution, accounting for decrease in marginal probability of closing triplet</td>
</tr>
<tr>
<td>CTRIPLE</td>
<td>![C triple Visualization]</td>
<td>$\sum_{i&lt;j,k \neq k} y_{ij}y_{jk}y_{ki}$</td>
<td>Sum of all cyclic triples in network</td>
</tr>
</tbody>
</table>
person C. Therefore, the **twopath** term is a structural precursor for a number of other configurations, including transitive closure and cycles. As such, including **twopath** in an ERGM assures structural control for more advanced configurations. A significantly positive/negative **twopath** term represents more/less propensity of actors in the network to both send and receive ties than random chance.

The **gwidegree** and **gwodegree** terms stand for geometrically-weighted in- and out-degree, respectively. In-degree represents the number of ties a person receives, while out-degree represents the number of ties a person sends. These terms were born out of necessity when fitting early ERGMs with Markov graphs, since simple in- and out-degree counts were not sufficient to obtain ERGM convergence (Handcock, 2003; Goodreau et al., 2009). The geometric weighting stands for a geometric series that inversely weights the value of in- and out-degree as an actor's count on the statistic increases (Hunter, 2007). It can be thought of in marginal value terms: the greater one's in- or out-degree count rises, the less marginal value the extra degree brings to the person. In essence, though adding one additional in-degree for a person that has one tie versus a person who has nine is equivalent, the geometric weighting favors the addition of the second in-degree more highly than that of the tenth in-degree (Snijders et al., 2006; Hunter, 2007; Robins et al., 2007b).

A significantly positive/negative **gwidegree** represents more/less preferential popularity in the network than random chance. That is, there is preference towards particular individuals in the network to attract many nominations (positive significance) or for all individuals to be roughly similar in popularity (negative significance). A significantly positive/negative **gwodegree** has a similar interpretation, but for sending, instead of receiving, ties. This is termed “activity” in the networks literature (Robins et al., 2007a; Koskinen and Daraganova, 2013).

The **gwesp** term stands for geometrically-weighted edgewise shared partner. Similar to **gwidegree** and **gwodegree**, **gwesp** relies on geometrically-weighted series to account for transitive closure within the network. Transitive closure represents the network tendency of a friend of a friend to also be a friend (Christakis and Fowler, 2007; Goodreau
et al., 2009). It represents a higher-order structural statistic within a network since it is dyad-dependent (Schaefer et al., 2010). To understand the meaning of the GWESP term, one could think of it in terms of marginal probability; while the probability of becoming friends with a friend’s friend increases with each additional friend in common, it does so at a decreasing rate. If by the tenth friend in common, person A and person B are still not friends, the marginal probability of becoming friends by adding an eleventh friend in common is less than with the addition of previous friends. The introduction of the GWESP term in ERGMs estimation was to help with model convergence. A significantly positive/negative GWESP term represents more/less triadic closure within the network than is expected by chance.

Finally, the CTRIple term represents cyclicality within the network. Cyclicality is representative of generalized – as opposed to hierarchical – exchange within the network. In an environment where hierarchy may be an important structural component (such as a co-worker network), then cyclicality is likely negative; however, where hierarchy is less important, then generalized exchange may be more prevalent. Therefore, a significantly positive/negative CTRIple term represents more/less generalized exchange within the network.

Table 3.2 presents four types of network compositional parameters. Unlike the structural parameters in table 3.1, compositional terms are dependent not just on ties, but on actor attributes, such as age, gender, language/math achievement, or geographic proximity to one another. The first of these parameters are homophily terms, namely, MATCH and ABDIFF.

The MATCH and ABDIFF terms both represent homophily between actors connected by ties in the network. A MATCH term in ERGMs would be used when the attribute is dichotomous or categorical, while the ABDIFF term is reserved for continuous variables. With MATCH, the statistic represents the sum of all attribute matches between actors in the network with ties; so, for example, if one is interested in gender homophily in the network with respect to ties, then the MATCH term on gender will represent the sum of all ties between same-sex actors. If desired, this can be disaggregated into respective
Table 3.2. Description of Directed Compositional Statistics for an Exponential Random Graph Models

<table>
<thead>
<tr>
<th>Statistic</th>
<th>Visualization</th>
<th>Formula</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>MATCH,</td>
<td></td>
<td>$\sum_{i,j} y_{ij} \mathbb{1}{D_i = D_j}$,</td>
<td>For dichotomous or categorical variables, sum of dyads matched on specified attribute; for continuous variables, absolute difference of specified attribute for dyads</td>
</tr>
<tr>
<td>ABSDIFF</td>
<td></td>
<td>$\sum_{i,j}</td>
<td>D_i - D_j</td>
</tr>
<tr>
<td>NODEOCOV</td>
<td></td>
<td>$\sum_{i,j} y_{ij} D_i$</td>
<td>Sum of attribute value for senders</td>
</tr>
<tr>
<td>NODEICOV</td>
<td></td>
<td>$\sum_{i,j} y_{ij} D_j$</td>
<td>Sum of attribute value for receivers</td>
</tr>
</tbody>
</table>

Genders. A significantly positive/negative MATCH term represents more/less homophily on the particular attribute within the network.

The ABSDIFF term also represents homophily, but for continuous variables. Rather than matching exact values of the attribute (e.g., gender), the ABSDIFF term calculates the sum of absolute differences between attribute values of two actors connected by a tie. Therefore, with a negatively significant ABSDIFF parameter, there is more homophily on the particular attribute within the network, whereas a positively significant ABSDIFF parameter represents less homophily on the attribute.

The NODEOCOV and NODEICOV terms represent the propensity of actors with a certain attribute to send or receive ties, respectively. So, for example, do boys tend to send (NODEOCOV) more ties than girls? Do girls tend to receive (NODEICOV) more ties than boys? These terms can be used with dichotomous as well as continuous data; there is
an equivalent term for categorical variables (not presented). Unlike the \texttt{MATCH/ABSDIFF}


terms, \texttt{NODEOCOV/NODEICOV} terms are not dependent on the other person in the dyad.
A significantly positive/negative \texttt{NODEOCOV} term represents more/less activity by nodes
with the particular attribute being measured. Conversely, for \texttt{NODEICOV}, a significantly
positive/negative term represents more/less popularity by nodes with the particular at-
tribute being measured.

### 3.1.3 ERGMs: Goodness-of-Fit Statistics

The MCMC maximum likelihood estimation of ERGMs will lead to one of three results
– a converged model or an unconverged model. A model that converges is one where a
maximum likelihood value for the network, given the specified parameters, is attained. A
unconverged model may represent either a degenerate network where a maximum likeli-
hood is not possible (Snijders, 2002; Robins et al., 2007b; Koskinen and Snijders, 2013)
or a network that needs a better specified MCMC process to reach convergence. One
source of degeneracy is a model with ill-specified effects. In fact, prior to the advent of
the geometrically-weighted ERGM terms, strong transitivity or higher levels of popularity
and/or activity would lead to degenerate networks with regularity (Snijders et al., 2006).

If a model does converge, it is important to next check the goodness-of-fit statistics for
the estimated network model.

Given the stochastic nature of an MCMC process, the draws from a MCMC process
are dependent upon the realization that began the process, initial starting values, and the
correlation between draws. Therefore, an intermediate step prior to assessing goodness-
of-fit is checking how well the MCMC process performed (Koskinen and Snijders, 2013).

These MCMC diagnostic tools include statistics on the whether the lags were correlated
with starting values (ideally, little correlation), whether mean/variance on parameters
were stationary over time, and normalized kernel density of parameters to assess normality
(i.e., another measure of stationarity) (Handcock et al., 2013b).

These diagnostics provide qualitative evidence on whether or not the MCMC process
simulated random draws that are comparable to the realized network. Assuming the
MCMC diagnostics are acceptable, then one can next assess the goodness-of-fit of the

81
model. If the diagnostics indicate significant differences between draws and the realization or significant correlation between the starting value and various lags, then re-estimation with a longer burn-in, greater number of draws, and/or greater distance between draws is advisable (Koskinen and Snijders, 2013).

As with any statistical model, estimation and inference is only as reliable as the fit of the model. If the model fit is poor, then estimates have less value in addressing questions of interest. For ERGMs, the goodness-of-fit diagnostics are still in development (Goodreau, 2007). The main approach being used is to simulate networks from the estimated statistics and create distributions for terms that are not modeled (Hunter et al., 2005; Koskinen and Snijders, 2013; Robins and Lusher, 2013). While any structural term could be used in assessing the goodness-of-fit, Hunter et al. (2005) proposed the use of basic structural tendencies that help to explain various aspects of the network; these included the degree distribution (both in and out), edgewise shared partners (or, transitive closure), dyadwise shared partners (or, two paths) and the triad census (or, the unique configuration of ties of three actors).

While these goodness-of-fit statistics are calculated mathematically, evidence of fit is often presented graphically in the form of parameter distributions. The simulation of the network statistics are compared with the actual value observed in the network to assess whether or not the model estimates do an adequate job capturing the measured statistic (Hunter et al., 2005; Goodreau, 2007). Mathematically, if \[
\left| \frac{\bar{S}_k(x_{\text{obs}}) - \bar{S}_k(x)}{SD(\bar{S}_k(x))} \right| \leq 2,
\] then the fit for the particular statistic, \(S_k\), is adequate (Robins et al., 2009; Koskinen and Snijders, 2013). Note, \(\bar{S}_k(x)\) and \(SD(\bar{S}_k(x))\) stand for the mean and standard deviation of \(S_k\), respectively.

### 3.1.4 Use of ERGM Parameter Estimates

While ERGMs provide a convenient and powerful way to assess the importance of structural and compositional phenomena within a network, they have certain drawbacks. First, estimates between networks are not strictly comparable. Unless individual networks are combined into one network – with structural zeros (representing the impossibility of a tie) between actors from different networks – network models are fit independent of one
another. Second, since ERGMs are a tie-based model, they do not provide information on actors’ non-tie-based attributes.

Since the ultimate outcome of this manuscript is to understand the role networks have on children’s academic achievement, I propose to use ERGM results from the 31 villages in the following way. I intend to use the $t$-statistic for parameter estimates as a continuous variable. While parameter estimates are not comparable across networks, the significance – as signified by the $t$-statistic – of particular parameters is comparable. For example, if transitive closure (GWESP) is significant in village 1 and village 2, the parameter estimates from village 1 and village 2 are not comparable; however, the fact that both villages display significant transitive closure is comparable. This way, I will have a distribution on each estimated parameter, scaled by its standard error, that allows for magnitudes of comparison between networks.

To my knowledge, using ERGM estimates in this manner is novel. While the use of meta-analysis has been used often to estimate the overall importance of structural effects across a variety of similar networks (Lubbers and Snijders, 2007) (e.g., classrooms within schools), little has been done to relate structural and compositional network effects back to the level of the actor. However, the approaches outlined above as well as other promising work on hierarchical network models (Sweet et al., 2013) may add to already-established techniques of aggregating information on structural and compositional characteristics across networks. This treatment provides information at the village level. To be able to correctly estimate effects at the child level, I next turn to multi-level modeling to identify important predictors of the outcomes of interest – child achievement, specifically, math and language performance.

3.2 Multi-Level Models

Multi-level models (MLMs) are a class of generalized linear models that allow one to model dependence between respondents within groups (Snijders and Bosker, 1999). These models seek to describe the amount of variation in the model explained between- and within-groups. The within-group variation is at the micro-unit (e.g., respondent-level),
while the between-group variation is at the macro-unit (e.g., at the group-level). For example, in school, students (the micro-unit) may be grouped within classes (the macro-unit) and any particular student’s performance is a function of both personal ability as well as shared effects between other respondents within the macro-unit, such as teacher ability, classroom resources, or the classroom environment. Ultimately, one might want to know to what extent did student ability play in classroom achievement; a MLM allows one to understand the contribution of student ability as well as group-level factors on student achievement.

The use of MLMs is diverse, from modeling educational outcomes (Lubbers, 2003; Lubbers et al., 2006; Almquist, 2011) to drug-using networks (Snijders et al., 1995). Moreover, an arbitrary number of levels can be modeled, depending on the hierarchical structure of the data. For this manuscript, there were three levels: children nested within households nested within villages. The use of a MLM is appropriate when the outcome of interest is at the micro-unit; if the outcome is at the macro-unit, then the within-group variation is of little concern (Snijders and Bosker, 1999).

The most basic form of a MLM is the random-intercept model, which allows for differences in intercept based on group membership, but constraints linear fits within groups to the same slope (Snijders and Bosker, 1999). For example, if a random-intercept model was being used to model student achievement with students nested within classrooms, one might expect to see certain classrooms with a higher intercept (representing greater endowment at the group level) and others with a lower intercept, but the slope of each of those linear fits (one per classroom modeled) would be the same, representing the mean-level individual ability between classrooms. Mathematically, the random-intercept model is represented as:

\[
Y_{ij} = \gamma_{00} + \sum_{h=1}^{p} \gamma_{h0} x_{hij} + \sum_{k=1}^{q} \gamma_{0k} z_{kj} + U_{0j} + \epsilon_{ij},
\]  

(3.2)

where respondent \(i\) is in group \(j\), with micro-unit explanatory variables, \(x\), and macro-unit explanatory variables, \(z\). The regression coefficients, \(\gamma_{00}, \gamma_{h0}\), where \((h = 1, \ldots, p)\), and \(\gamma_{0k}\), where \((k = 1, \ldots, q)\), represent the group-level intercept, micro-unit explanatory
variables, and macro-unit explanatory variables, respectively. Moreover, $Y_{ij}$ represents the outcome of interest for each respondent $i$ within each group $j$; $U_{0j}$ represent group-dependent random error terms, and $\varepsilon_{ij}$ represents individual-dependent random error in the model. The $U_{0j}$ and $\varepsilon_{ij}$ terms comprise the random part of the random-intercept model in Equation 3.2, while the $\gamma$, $x$, and $z$ components represent the fixed portion of the model (Snijders and Bosker, 1999).

Of considerable importance in random-intercept models – and in fact, any MLM – is the comparison of individual- and group-level variance. Beyond simply calculating parameters correctly, it is important to understand at what level variation is driving results. Both $U_{0j}$ and $\varepsilon_{ij}$ are assumed to be independently, normally distributed random variables with mean zero and variances $\sigma^2$ and $\tau^2_0$, respectively. The correlation of these two variance measures provides evidence towards the amount of variability in the outcome attributable to macro- and micro-unit factors. The intraclass correlation coefficient (ICC) is defined as

$$\rho_I (Y|X) = \frac{\tau^2_0}{\sigma^2 + \tau^2_0}. \quad (3.3)$$

The ICC in Equation 3.3 relates how much of the variance in the particular model is attributable to the group-level. In a two-level model, $1 - \rho_I (Y|X)$ provides the residual variance at the individual level.

While the random-intercept model is adequate to represent differences between groups, occasionally, one might believe that individual-level differences drive differences within groups too. In this case, one might employ a random-slope model that allows for both intercept differences at the group level, as well as slope differences at the individual level, based on an individual-level variable. For example, one may believe gender differences to be an important distinction when modeling academic achievement. Therefore, modeling students within classrooms can include a random intercept to account for classrooms as well as a random slope to account for gender differences. This can be modeled as:
\[ Y_{ij} = \gamma_{00} + \sum_{h=1}^{p} \gamma_{h0}x_{hij} + \sum_{k=1}^{q} \gamma_{0k}z_{kj} + \sum_{k=1}^{q} \sum_{h=1}^{p} \gamma_{hk}z_{kj}x_{hij} + U_{0j} + \sum_{h=1}^{p} U_{hj}x_{hij} + \varepsilon_{ij}, \]

(3.4)

where, in addition to terms common to the random-intercept model, Equation 3.4 adds parameter terms for \( \gamma_{hk} \), representing slope effects for individual attribute \( h \) within group \( k \) in the fixed portion of the model. Moreover, in the random portion of the model, there is a new random term, \( U_{hj}x_{hij} \), representing random error for individual attribute \( h \) in group \( k \) (Snijders and Bosker, 1999).

The use of a random-intercept versus a random-slope model must balance the need for greater explanatory power with a parsimonious model. Random slope terms are justified to examine variables that have a known influence on the outcome; for example, age or intelligence might be related in relevant ways to academic achievement (Snijders and Bosker, 1999). However, specifying a model that allow all individual-level variables to have a random slope is probably not justified. Moreover, the hierarchical nature of the model can also induce greater complexity; in a three-level model, there can be random slopes at both the respondent and first group level, with random intercepts at the first and second group levels. Each greater level of specificity adds complexity to the model, which needs to be balanced with both subject-matter expertise and a parsimonious explanation of results (Snijders and Bosker, 1999).

3.3 Analytic Strategy

By describing both ERGMs and MLMs, I now outline my analytic strategy in estimating environmental, structural, and cognitive factors (see figure 2.1) on academic achievement. First, cognitive and structural effects are modeled by village using ERGMs. These ERGMs will specify – for each village – a standard model of structural and compositional network terms that represent structural impact and social cognition, respectively. After estimating ERGMs, I will check both the MCMC diagnostics and ERGM goodness-of-fit statistics to ensure a valid and sound model for the data. Second, I will extract the \( t \)-statistic for
each ERGM parameter estimate to create parameter distributions across villages. These provide evidence – at the village level – of network structure and social cognition to fit within a series of MLMs, relying on literature in sections 2.2.2 and 2.2.3 for model terms.

Turning to the MLMs, I will estimate a three-level model of children, nested within households, nested within villages. I will start with a random-intercept model, modeling each of the two outcomes – math achievement and language achievement – separately. Next, I will estimate a random-slope model that utilizes indegree and outdegree of children. I utilize the degree distribution to allow for differing network position as a function of the outcome. These effects stem from literature in sections 2.2.1 and 2.2.2, while the combination of ERGM/MLM seeks to understand network effects on interventions (section 2.2.4).

This plan will serve as the basis for my analysis and circles back to the important precursors of behavioral decisions as modeled in figure 2.1. I intend to model a system of environmental factors – such as household socio-economic status, education of the head of household, and village norms – along with network structure – such as reciprocity and transitive closure – and social cognition of children, as captured by homophily and sender/receiver effects on child performance.

### 3.4 Computational Software

With respect to both ERGM and MLM estimation, I used R 3.0.0 for estimation (R Core Team, 2013). R is an open-source, general-purpose statistical programming environment that contains a variety of core functions to estimate a wide number of statistical models. However, for specialized analyses, like ERGMs and MLMs, there are additional packages that can be used. For ERGMs, I utilized the statnet 3.1-0 suite of network tools (Handcock et al., 2013b), which includes the ergm 3.1-0 package (Handcock et al., 2013a) specifically for ERGM estimation. The parameter names discussed in Tables 3.1 and 3.2 relate to the parameter terms used in the ergm package. For MLM estimation, I used the lme4 0.999999-2 package (Bates et al., 2013). Resulting tables from ERGM and MLM estimations are created using the stargazer 4.5.3 (Hlavac, 2014) and xtable 1.7-
packages, while graphics have been created with the \texttt{ggplot2 0.9.3.1} package (Wickham and Chang, 2012).
Chapter 4

Results

This chapter presents results of the exponential random graph model (ERGM) and multilevel model (MLM) estimations outlined in chapter 3. Results indicated that across the 31 playmate networks, there were common ERGMs with strong convergence and a consistently good fit. Moreover, from the MLMs, network structure and composition had an impact on student achievement, adding additional information to the intervention results discussed in Burde and Linden (2012, 2013). The chapter proceeds with descriptive statistics on the villages, households, and children in the study – including an analysis of isolates – in section 4.1, while in section 4.2, descriptive statistics about network structure are discussed. Next, ERGM estimations and goodness-of-fit statistics are presented in section 4.3. Finally, MLMs relating village, household, and child characteristics to math and language achievement – including network structure and composition – are presented in section 4.4 while section 4.5 concludes.

4.1 Demographic Descriptive Statistics

While at baseline, random assignment to the treatment and control statuses is expected to lead to few significant differences between groups, the comparisons presented here are for data after the implementation of the intervention. Baseline data, due to difficulties encountered in the field, were incomplete. For static variables – like children’s gender – whether at baseline or post-intervention follow-up, there should be few differences. For variables affected by the intervention – like years of education or current attendance – one
should expect differences in favor of the treatment group.

Tables 4.1, 4.2, and 4.3 explore village-, household-, and child-level variables between treatment and control groups, respectively. Each table presents the mean on selected variables by treatment group, with a t-test for significance between treatment and control groups. Overall, there were few statistical differences at the 0.05 level between groups. For additional demographic comparisons, see Burde and Linden (2012).

The size of villages and the network composition were compared at the village level. First, the number of households per village did not differ significantly, though there were significantly more children overall in treatment villages. Because social network measures are related to the total number of actors within a particular network, all of the network measures in table 4.1 have been normalized to be comparable across networks. For both playmate and friendship networks, density was significantly greater in control villages than treatment villages. Density measures the proportion of possible ties that were present in the network; the playmate networks were also more dense than the friendship networks.

<table>
<thead>
<tr>
<th>Table 4.1. Village Demographics by Treatment Status</th>
<th>Treatment</th>
<th>Control</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>13</td>
<td>18</td>
<td></td>
</tr>
<tr>
<td>Mean Number of Households</td>
<td>30.462</td>
<td>21.167</td>
<td>0.061</td>
</tr>
<tr>
<td>Mean Number of Children</td>
<td>59.462</td>
<td>37.944</td>
<td>0.017</td>
</tr>
<tr>
<td>Mean Playmate Network Density</td>
<td>0.049</td>
<td>0.079</td>
<td>0.033</td>
</tr>
<tr>
<td>Mean Playmate Degree Centralization</td>
<td>0.070</td>
<td>0.082</td>
<td>0.262</td>
</tr>
<tr>
<td>Percent Isolates, Playmate Network</td>
<td>0.046</td>
<td>0.037</td>
<td>0.579</td>
</tr>
<tr>
<td>Mean Friendship Network Density</td>
<td>0.024</td>
<td>0.039</td>
<td>0.041</td>
</tr>
<tr>
<td>Mean Friendship Degree Centralization</td>
<td>0.050</td>
<td>0.065</td>
<td>0.173</td>
</tr>
<tr>
<td>Percent Isolates, Friendship Network</td>
<td>0.133</td>
<td>0.128</td>
<td>0.851</td>
</tr>
</tbody>
</table>

Degree centralization, or the amount to which networks ties were centered on certain individuals, provides a sense of whether network ties were dispersed evenly across actors in the network or heavily concentrated on network “stars.” In other words, while density measures the proportion of ties in the network – much like the mean of a variable
degree centralization is a measure of dispersion within the network – much like the standard deviation of a variable. In both playmate and friendship networks, the level of centralization was low (higher dispersion of ties) and did not differ between treatment status. This indicates there were few “stars,” or children whom everyone else considered a playmate/friend.

Finally, there were no differences between the number of isolates between treatment and control villages for either the playmate or the friendship networks. The playmate network, in addition to having greater connectivity, as measured by density, had fewer isolated individuals, or children who had no connections to other children in the village. The issue of isolates – both by treatment status and by isolated versus non-isolated children – was explored in greater depth in tables 4.4 and 4.5.

In table 4.2, households living in treatment villages lived on average more than two years longer in their present location than those in the control villages, a significant difference. However, in terms of how households self-identified, there were no differences between treatment and control villages. The majority of households were involved in farming, though those in control villages were significantly more likely to be involved in day labor.

The demographics of the head of household for treatment and control villages did not differ. In both groups, the head of household had relatively little schooling (about three years) and the size of the household was quite similar (about six people). Treatment households seemed better off socio-economically; they ate meat significantly more often than control households and owned a significantly greater number of sheep, both proxies for socio-economic status. However, even though treatment households ate meat significantly more than control households, more than half (about 55 percent) of treatment village households ate meat less than once a month and about 65 percent of control village households ate meat less than once a month, indicating in absolute terms, a paucity of resources amongst all households.

Finally, there were significant differences in the number of children per treatment and control households as well as the number of households without children; however, the
Table 4.2. Household Demographics by Treatment Status

<table>
<thead>
<tr>
<th></th>
<th>Treatment</th>
<th>Control</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>680</td>
<td>667</td>
<td></td>
</tr>
<tr>
<td>Mean Years in Village</td>
<td>28.009</td>
<td>26.150</td>
<td>0.043</td>
</tr>
<tr>
<td>Percent Farsi-speaking</td>
<td>0.212</td>
<td>0.208</td>
<td>0.848</td>
</tr>
<tr>
<td>Percent Ethnic Tajik</td>
<td>0.269</td>
<td>0.227</td>
<td>0.082</td>
</tr>
<tr>
<td>Percent Afghan Citizen</td>
<td>0.050</td>
<td>0.057</td>
<td>0.614</td>
</tr>
<tr>
<td>Percent Ethnic Aimaq</td>
<td>0.292</td>
<td>0.296</td>
<td>0.888</td>
</tr>
<tr>
<td>Percent Other Background</td>
<td>0.176</td>
<td>0.213</td>
<td>0.100</td>
</tr>
<tr>
<td>Percent Farmer</td>
<td>0.748</td>
<td>0.726</td>
<td>0.373</td>
</tr>
<tr>
<td>Percent Day Laborer</td>
<td>0.091</td>
<td>0.135</td>
<td>0.013</td>
</tr>
<tr>
<td>Mean Head of Household (HoH) Age</td>
<td>38.030</td>
<td>37.637</td>
<td>0.600</td>
</tr>
<tr>
<td>Mean HoH Years of Education</td>
<td>2.932</td>
<td>2.779</td>
<td>0.413</td>
</tr>
<tr>
<td>Mean People in Household (HH)</td>
<td>6.632</td>
<td>6.071</td>
<td>0.001</td>
</tr>
<tr>
<td>Percent HHs Eat Meat More than Monthly</td>
<td>0.415</td>
<td>0.318</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean Jeribs of Irrigated Land</td>
<td>1.346</td>
<td>1.167</td>
<td>0.083</td>
</tr>
<tr>
<td>Mean Number of Sheep</td>
<td>7.069</td>
<td>5.008</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean Number of Children</td>
<td>1.316</td>
<td>1.171</td>
<td>0.034</td>
</tr>
<tr>
<td>Percent HHs Without Children</td>
<td>0.349</td>
<td>0.382</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean Age Boys Should Stop Education</td>
<td>21.167</td>
<td>21.264</td>
<td>0.672</td>
</tr>
<tr>
<td>Mean Age Girls Should Stop Education</td>
<td>15.344</td>
<td>14.917</td>
<td>0.015</td>
</tr>
</tbody>
</table>

practical significance of both results – a tenth of a child difference in favor of treatment villages and a 3 percentage-point difference in households without children in favor of the control villages – likely has little practical significance.

Interestingly, while households in treatment and control villages displayed little difference in opinion about when boys should stop going to school, the groups differed with respect to girls. Treatment villages believed girls should attend school longer, which may reflect bias from the additional educational opportunities open in the treatment locales.

Detailed information was collected just of children ages six to 11 in villages, though
other children were recorded when determining household size (see Table 4.2). This was a function of the PACE-A target population; the intervention was designed for children who would be starting school with PACE-A, which were those between the ages of six and 11. See Table 4.3 for full results.

<table>
<thead>
<tr>
<th>Table 4.3. Child-level Demographics by Treatment Status</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
</tr>
<tr>
<td>--------------------------------</td>
</tr>
<tr>
<td>N</td>
</tr>
<tr>
<td>Percent Son of Head of Household (HoH)</td>
</tr>
<tr>
<td>Percent Daughter of HoH</td>
</tr>
<tr>
<td>Percent Niece/Nephew of HoH</td>
</tr>
<tr>
<td>Percent Sibling of HoH</td>
</tr>
<tr>
<td>Percent Other Relation to HoH</td>
</tr>
<tr>
<td>Percent Girls</td>
</tr>
<tr>
<td>Mean Age of Children</td>
</tr>
<tr>
<td>Mean Years of Education for Children</td>
</tr>
<tr>
<td>Percent Children Currently Attending School</td>
</tr>
<tr>
<td>Percent of Children Not Working</td>
</tr>
<tr>
<td>Mean Raw Math Score (0-3)</td>
</tr>
<tr>
<td>Mean Raw Language Score (0-3)</td>
</tr>
<tr>
<td>Mean Playmate Network Indegree</td>
</tr>
<tr>
<td>Mean Friendship Network Indegree</td>
</tr>
</tbody>
</table>

According to table 4.3, about half of the children in the household were the children of the head of household, with the rest being a mix of nieces and nephews, siblings, and others (such as grandchildren). A little less than half the sample were girls and the mean age of children was about eight and one-third years, which was not unexpected, given data were only of children between the ages of six and 11. Finally, children had a moderate level of education for their age (a little more than one year).

In all likelihood, the difference in the percentage of children currently attending school between treatment and control villages was driven by the opening of the CBSs in treatment
villages by the time surveying commenced. Because of this, one would expect a significant difference. Also note, the question did not differentiate types of education with respect to attendance, so some of those who answered affirmatively may be indicating attendance at a mosque school, as opposed to formal education. Likewise, differences between achievement scores in mathematics and language was a bivariate indication of treatment success of the PACE-A program.

Finally, indegree measures the number of ties that a child received from others in the network. Since density was higher in the playmate network, average indegree was by definition higher too. Moreover, there was a significant difference between treatment and control villages with respect to indegree in the playmate – but not the friendship – network, with children in treatment village on average receiving 2.4 playmate nominations compared to 2.2 in the control villages. The substantive value of that difference, however, is questionable.

In any network, isolates represent a special case of actor. They are completely disconnected within the network, indicating they do not influence – nor are influenced by – others. So while the percentage of isolated did not differ between treatment and control groups, since they represent close to five percent of children overall, it is instructive to look closer at these children’s characteristics.

In the case of these playmate networks, two additional analyses of isolates were completed. The first (table 4.4) investigated child-level differences of isolates between the treatment and control groups, while the second (table 4.5) explored differences between isolated and non-isolated children across villages. Both tables 4.4 and 4.5 compare the same child-level characteristics as table 4.3. In the playmate networks, 4.2 percent of children were isolates.

While there is a large amount of variation in point estimates between isolates in the treatment and control groups (see table 4.4), there were few statistically significant differences. However, isolates in control villages tended to have lower language scores than isolates in treatment villages. With few differences between treatment groups, table 4.5 explores differences between isolated children and non-isolated children across all villages.
Table 4.4. Isolates Child-level Demographics by Treatment Status

<table>
<thead>
<tr>
<th></th>
<th>Treatment</th>
<th>Control</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>35</td>
<td>27</td>
<td></td>
</tr>
<tr>
<td>Percent Son of Head of Household (HoH)</td>
<td>0.571</td>
<td>0.370</td>
<td>0.120</td>
</tr>
<tr>
<td>Percent Daughter of HoH</td>
<td>0.343</td>
<td>0.593</td>
<td>0.051</td>
</tr>
<tr>
<td>Percent Niece/Nephew of HoH</td>
<td>0.029</td>
<td>0.000</td>
<td>0.384</td>
</tr>
<tr>
<td>Percent Sibling of HoH</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Percent Other Relation to HoH</td>
<td>0.057</td>
<td>0.037</td>
<td>0.720</td>
</tr>
<tr>
<td>Percent Girls</td>
<td>0.343</td>
<td>0.593</td>
<td>0.051</td>
</tr>
<tr>
<td>Mean Age of Children</td>
<td>8.029</td>
<td>7.741</td>
<td>0.530</td>
</tr>
<tr>
<td>Mean Years of Education for Children</td>
<td>1.200</td>
<td>0.944</td>
<td>0.425</td>
</tr>
<tr>
<td>Percent Children Currently Attending School</td>
<td>0.600</td>
<td>0.370</td>
<td>0.075</td>
</tr>
<tr>
<td>Percent of Children Not Working</td>
<td>0.200</td>
<td>0.037</td>
<td>0.059</td>
</tr>
<tr>
<td>Mean Raw Math Score (0-3)</td>
<td>1.211</td>
<td>0.733</td>
<td>0.060</td>
</tr>
<tr>
<td>Mean Raw Language Score (0-3)</td>
<td>1.143</td>
<td>0.602</td>
<td>0.036</td>
</tr>
<tr>
<td>Mean Playmate Network Indegree</td>
<td>0.000</td>
<td>0.000</td>
<td></td>
</tr>
<tr>
<td>Mean Friendship Network Indegree</td>
<td>0.029</td>
<td>0.000</td>
<td>0.384</td>
</tr>
</tbody>
</table>

Compositionally, isolates and non-isolates only differed by age. Isolates tended to be significantly younger, by almost half a year. This should have effects on school-related measures, which was the case: isolates were less likely to be attending school, performed significantly worse in both math and language, and had fewer friends. Not unexpectedly, isolates differed significantly from non-isolates in terms of the number of children who nominated them as a playmate. Together, tables 4.4 and 4.5 present an interesting picture of achievement. While treatment isolates performed significantly better in language (and qualitatively better in math) than control isolates, isolates in general performed significantly worse than non-isolates in both math and language, indicating that while the PACE-A intervention was successful in increasing learning, there are certainly peer effects that were important in differentially increasing achievement.

Across village-, household-, and child-level demographics, there was broad balance
Table 4.5. Child-level Demographics of Isolates

<table>
<thead>
<tr>
<th></th>
<th>Isolate</th>
<th>Non-Isolate</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>N</td>
<td>62</td>
<td>1394</td>
<td></td>
</tr>
<tr>
<td>Percent Son of Head of Household (HoH)</td>
<td>0.484</td>
<td>0.467</td>
<td>0.795</td>
</tr>
<tr>
<td>Percent Daughter of HoH</td>
<td>0.452</td>
<td>0.456</td>
<td>0.943</td>
</tr>
<tr>
<td>Percent Niece/Nephew of HoH</td>
<td>0.016</td>
<td>0.013</td>
<td>0.827</td>
</tr>
<tr>
<td>Percent Sibling of HoH</td>
<td>0.000</td>
<td>0.027</td>
<td>0.194</td>
</tr>
<tr>
<td>Percent Other Relation to HoH</td>
<td>0.048</td>
<td>0.037</td>
<td>0.654</td>
</tr>
<tr>
<td>Percent Girls</td>
<td>0.452</td>
<td>0.491</td>
<td>0.547</td>
</tr>
<tr>
<td>Mean Age of Children</td>
<td>7.903</td>
<td>8.341</td>
<td>0.041</td>
</tr>
<tr>
<td>Mean Years of Education for Children</td>
<td>1.089</td>
<td>1.240</td>
<td>0.307</td>
</tr>
<tr>
<td>Percent Children Currently Attending School</td>
<td>0.500</td>
<td>0.658</td>
<td>0.011</td>
</tr>
<tr>
<td>Percent of Children Not Working</td>
<td>0.129</td>
<td>0.099</td>
<td>0.441</td>
</tr>
<tr>
<td>Mean Raw Math Score (0-3)</td>
<td>1.003</td>
<td>1.572</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean Raw Language Score (0-3)</td>
<td>0.907</td>
<td>1.127</td>
<td>0.042</td>
</tr>
<tr>
<td>Mean Playmate Network Indegree</td>
<td>0.000</td>
<td>2.411</td>
<td>0.000</td>
</tr>
<tr>
<td>Mean Friendship Network Indegree</td>
<td>0.016</td>
<td>1.176</td>
<td>0.000</td>
</tr>
</tbody>
</table>

between treatment and control villages. Where differences existed, the practical significance is likely small or an artifact that can be controlled for within the MLMs. Next, section 4.2 presents descriptive statistics about the structural and compositional parameters of the playmate network. While the structural parameters represent the building blocks of an ERGM, accounting for basic network tendencies, as discussed in Lusher and Robins (2013), the compositional parameters indicate similarity and are precursors to understanding influence and selection in networks. Refer to tables 3.1 and 3.2 for pictorial, definitional, and mathematical definitions of parameter terms.

4.2 Network Structure Descriptive Statistics

Since network structure is calculated on a network-by-network basis, presenting traditional descriptive statistics is difficult. Therefore, information on network structure across vil-
lages is presented as a series of box-and-whisker plots (see figures 4.1 through 4.5). All figures represent the playmate networks in the 31 villages and the ends of the boxes represent the interquartile range of the data, while the horizontal line inside the box represents the median value. The end of the whiskers represent 1.5 times the interquartile range from the edge of the box and red dots represent outliers.

However, because the count statistics below are entirely dependent on network size, each of the counts have been rescaled to be a percentage of the theoretical maximum for each statistic. Note, because of this, the edges term actually represents network density, since the count of edges in a network divided by the theoretical maximum number of edges is density.

Figure 4.1 presents the lower end of the indegree distribution. For example, $\text{idegree0}$ is the percentage of individuals with zero indegree, or isolates, whereas $\text{idegree1}$ is the percentage of individuals with an indegree of one.

At the low end of the indegree distribution, there seemed to be little difference between the treatment groups. Note, however, over 20 percent of children in each group received no nominations from others. By an indegree of four, there was slight separation between the treatment and control villages, though overlap between the groups is still evident.

For the outdegree distribution, a little less than 10 percent of children in both treatment and control groups gave no nominations. There is a clear peak at an outdegree of two for both treatment and control groups. Overall, the outdegree distribution seems quite similar between the two groups; control villages’ children tended to be lower on the outdegree distribution, but not significantly; see figure 4.2.

Figure 4.3 includes the compositional terms of the model – $\text{abssdiff.lang}$ (language homophily), $\text{abssdiff.math}$ (math homophily), and $\text{nodematch.gender}$ (gender homophily) – along with the edges term. Again, the edges term represents density, since it is normalized. Control villages showed a higher density (see, as well, table 4.1) than treatment villages, as well as a higher propensity towards gender homophily. That is, in control villages, playmate ties between children were more likely to be within the same gender (i.e., girl/girl or boy/boy) than across genders.
In terms of performance, the absolute difference terms measure the difference between two children with a playmate tie on math/language performance. That is, if two children scored the same on the math assessment, then their absolute difference would be 0; if they were drastically different in terms of math ability, their difference would be quite large. Therefore, in both treatment and control groups, there were similar levels of deviation between children with playmate ties with respect to math; however, in terms of language,
in the control group, there was significantly more variation between children’s performance in the control group.

Note, because the homophily and absolute difference terms are standardized over the theoretical maximum, the interpretation is somewhat obtuse. Rather than measure the amount of deviation, for example, of math ability on average, these normalized measures are percent of possible deviation over all villages within the treatment or control groups.
By looking at the counts within each individual villages, one can get a better sense of how much compositional difference there is between children with ties to one another.

Edgewise shared partners are a network term that measures the propensity towards triadic closure. Triadic closure represents a higher-order network effect from sending/receiving ties or reciprocating ties. As triangles of network members are closed, processes
Figure 4.4. Descriptive Statistics – Edgewise Shared Partners – Playmate Network

towards influence and selection increase. As with the indegree and outdegree distributions, figure 4.4 represents the percent of children with a given level of triadic closure in the networks.

At the low end of the edgewise shared partner distribution (see figure 4.4), control villages had two outlying villages that raised the median percentage of children with no triadic closure. Unlike an isolate in the indegree or outdegree distribution, zero triadic
closure does not mean children have no ties (though isolates will, by definition, have zero triadic closure), just that they do not have “friends of friends.” The general distribution, while not significantly different between treatment and control villages, does indicate that the level of network complexity in treatment villages may be a bit higher. One should note, very few children in either group have more than three edgewise shared partners, meaning that two individuals tend not to share more than three other individuals in common as playmates.

Figure 4.5, like figure 4.4, represents higher order structural terms in an ERGM specification. The mutual term represents reciprocity of playmate nominations, indicating both children in a playmate pair nominated the other as a playmate. This generally indicates a stronger tie than just one child sending a non-reciprocated tie to another. The twopath term is a precursor to the edgewise shared partners and cyclic triples terms as it creates the necessary conditions to either create a “friend of a friend” or close a cycle between three individuals (cyclic triple).

Cyclic triples represent tendency for generalized exchange; in other words, a lack of hierarchy in the network. For example, if Gery gives advice to Hank, who give advice to Dana, who gives advice to Gery, neither Gery, nor Hank, nor Dana is any more or less elevated in an advice context than the other. In figure 4.5, the percent of cyclic triples across the playmate networks are very low for both treatment and control groups, indicating, in general, little generalized exchange in the networks.

Given the low number of twopaths in the networks, it is unsurprising that there is little generalized exchange. Without having the precursor to generalized exchange, it is difficult to network to develop higher order structures. Note, with respect to twopaths, figure 4.5 indicates that there is slightly more twopaths in general in control villages, though still less than one percent of the theoretical number of twopaths possible. In terms of mutual ties though, there is a higher propensity towards reciprocating ties than there are to higher order structures like twopaths, but still the percentage of reciprocated ties is low, with little difference between treatment and control groups.

As with the descriptive statistics in section 4.1, there seem to be very few differences
between treatment and control villages in terms of network descriptives. The few differences that may exist are likely small and can be controlled for within both the ERGM and MLM specifications. Interestingly, there was little descriptive indication of higher order network structures playing a role in these children’s networks. Finally, on the compositional terms, such as gender and performance homophily, there seemed to be enough variation within the networks that these terms may demonstrate an association within
the ERGM and MLM outcomes.

4.3 Exponential Random Graph Model Estimations

Three common ERGMs were fit for each of the 31 playmate networks; first was a structural model, which included edges, mutual ties, twopaths, geometrically-weighted indegree (GWIndegree), geometrically-weighted outdegree (GWOOutdegree), geometrically-weighted edgewise shared partners (GWESP), and cyclic triples. This model only accounted for basic structural tendencies of the networks. The cognitive model expanded upon the structural model by adding the performance homophily terms for math and language, as well as a gender homophily term. The final model, termed the GIS (geographic information system) model, started with the structural model and incorporated geographic information on children into the ERGM model. It also included a homophily term to measure if children closer/further from school tended to play with other children that were closer/further from the school. The geographic information on children takes into account the physical distance between children with a tie to one another.\footnote{Note, using geographic positioning system (GPS) data on each household interviewed, the great-circle distance between two points was calculated between each and every household in the village using the haversine formula.}

Because each ERGM was fitted separately and was dependent on network size, parameter estimates and standard errors are not comparable across networks. However, the \(t\)-statistics – or the parameter estimate divided by the standard error – are comparable across networks, since it gives for each network parameter, the absolute extremity of the parameter. Table 4.6 presents the mean and standard deviation of the parameter terms for each of the estimated villages. Estimates with a large absolute magnitude tend to indicate that, across villages, these structural terms were significantly more/less likely (positive/negative parameter value, respectively) than chance observance in networks of the sizes estimated. Moreover, the larger the standard deviation, the larger the variance in the parameter estimates.

For each of the ERGM specifications, not all villages estimated and some of those that did estimate, did not converge. Non-estimation indicates that there were no pa-
<table>
<thead>
<tr>
<th>Variable</th>
<th>Structural</th>
<th>Cognitive</th>
<th>GIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (SD)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Networks Estimated (N (%))</td>
<td>30 (0.97)</td>
<td>25 (0.81)</td>
<td>29 (0.94)</td>
</tr>
<tr>
<td>Networks Converged (N (%))</td>
<td>27 (0.9)</td>
<td>24 (0.96)</td>
<td>28 (0.97)</td>
</tr>
<tr>
<td>Mean Time to Estimate (in Minutes)</td>
<td>15.57 (53.26)</td>
<td>4.87 (5.63)</td>
<td>7.67 (18.86)</td>
</tr>
<tr>
<td>Mean edges $t$-Statistic</td>
<td>-2.24 (1.05)</td>
<td>-4.68 (1.72)</td>
<td>-3.81 (1.56)</td>
</tr>
<tr>
<td>Mean mutual $t$-Statistic</td>
<td>2.81 (2.33)</td>
<td>3.02 (2.27)</td>
<td>2.3 (2.05)</td>
</tr>
<tr>
<td>Mean twopath $t$-Statistic</td>
<td>-2.01 (1.69)</td>
<td>-2.17 (1.48)</td>
<td>-2.61 (1.24)</td>
</tr>
<tr>
<td>Mean gwiddegree $t$-Statistic</td>
<td>0.14 (0.95)</td>
<td>0 (1.52)</td>
<td>0.16 (1.35)</td>
</tr>
<tr>
<td>Mean gwodegree $t$-Statistic</td>
<td>1.52 (0.76)</td>
<td>2.62 (1.28)</td>
<td>2.7 (1.34)</td>
</tr>
<tr>
<td>Mean gwesp $t$-Statistic</td>
<td>5.72 (2.97)</td>
<td>7.17 (3.47)</td>
<td>7.26 (3.56)</td>
</tr>
<tr>
<td>Mean ctriple $t$-Statistic</td>
<td>-0.53 (1.73)</td>
<td>-0.7 (1.95)</td>
<td>-0.94 (2.45)</td>
</tr>
<tr>
<td>Mean absdiff.math $t$-Statistic</td>
<td>-1.73 (1.22)</td>
<td>-2.26 (1.22)</td>
<td></td>
</tr>
<tr>
<td>Mean absdiff.lang $t$-Statistic</td>
<td>-0.85 (1.34)</td>
<td>-0.84 (1.12)</td>
<td></td>
</tr>
<tr>
<td>Mean nodematch.gender $t$-Statistic</td>
<td>3.95 (1.19)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean absdiff.near.school $t$-Statistic</td>
<td></td>
<td>1.03 (2.12)</td>
<td></td>
</tr>
<tr>
<td>Mean dyad.mutual $t$-Statistic</td>
<td>-2.3 (1.59)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean dyad.upper $t$-Statistic</td>
<td>-2.71 (1.91)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean dyad.lower $t$-Statistic</td>
<td>-2.87 (2.02)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Parameter estimates or the parameter estimates were likely degenerate for the particular village. Non-convergence indicates that village has estimated parameter terms for the network statistics, but it is likely not the maximum likelihood value, which the ERGM seeks through the Markov chain Monte Carlo (MCMC) method. I have opted to include estimated, but non-converged, networks in these results so as to maximize the amount of data for the MLM estimations later. The top of table 4.6 indicates the percentage of networks that estimated and converged, as well as the mean time to estimate each network for a particular model specification. In the cognitive model, there were six villages (villages 1, 5, 10, 20, 22, and 25) where there was complete gender segregation in terms of playmate ties. Therefore, because of the inclusion of the gender homophily term, the
ERGM was unable to estimate without producing degenerate parameter values.

Across models, table 4.6 and figures 4.6, 4.7, and 4.8 indicate that common parameter terms were signed in a similar fashion. Figures 4.6, 4.7, and 4.8 complement the results in table 4.6 by showing the $t$-statistic value needed to indicate an aggregate significant effect at the 0.05 level as horizontal lines in the figures. As discussed earlier, the box-and-whisker plots represent the interquartile range of the data, while the horizontal line inside the box represents the median value. The end of the whiskers represent 1.5 times the interquartile range from the edge of the box with outliers as black dots.

As discussed in chapter 3, while the parameter values of an ERGM represent the conditional log-odds of a tie, their real value is whether they are positive/negative and whether their $t$-statistic is significant at a given level. Since these results are an average of $t$-statistics, there is slightly more information here. For example, the average value for the edges term across villages and network specifications is greater than -1.96, which would indicate a significant term at the 0.05 level. In turn, this means that across villages and specifications, there was significantly less nominations sent in networks than one would expect by chance. This is a common result in many networks, since density of networks is usually well below 50 percent. The mutual term, however, indicates that of nominations sent, many were reciprocated. In figure 4.5, there were very few two-paths in the network; ERGM aggregate results (table 4.6) confirm that there were fewer two-paths than one would expect by chance.

In aggregate, there seemed to be little significance of the GWIndegree and cyclic triple terms across villages and model specifications (see figure 4.6). GWOutdegree was, in aggregate, significant for the cognitive and GIS specifications, indicating children sent more ties in these specifications than would be expected by change. Given the level of ties in the village, there was significantly more triadic closure than one would expect by chance. This seemingly contradicts the base amounts of edgewise shared partners in the descriptive statistics in figure 4.4. While the descriptive statistics might be considered akin to a bivariate regression result, the GWESP term is interpreted in the ERGM with respect to all other model parameters. The significant level of triadic closure indicated
that higher order network structure may be present in these networks after all.

For the cognitive and GIS models, compositional terms (see figure 4.7) were also added to the model. With respect to the absolute difference terms, as discussed in section 3.1.2, a significantly negative parameter value indicated homophily on the particular attribute, while a significantly positive parameter value indicated heterophily. This is due to the nature of the absolute difference – a smaller value indicates greater sameness, which
indicates a low value, and consequently, less difference than one would expect to see by chance (i.e., a negative parameter value in the ERGM). However, a larger difference leads to a larger value for the particular network, indicating more difference than one would expect to see by chance. In aggregate, there seemed to be an insignificant amount of homophily with respect to language performance, but an aggregate amount of math performance homophily in the GIS specification and a trending amount in the cognitive
specification. Unsurprisingly, in the cognitive specification, there was a high level of gender homophily in terms of children’s playmates; this is unexpected for this context and at this age in children’s networks.

For the GIS model, the three distance terms – dyad.mutual, dyad.upper, and dyad.lower – represent mutual, outgoing, and incoming ties from child-to-child, respectively. For each of the three types of ties between children in figure 4.8, distance played
an important role: as the distance between children increased, they were significantly less likely to be playmates, indicating that children’s playmates were physically closer to them than non-playmates. However, in table 4.7, the distance to school seemed to have little impact on the propensity for children to be playmates. That is, distance from school was not a significant factor in structuring their playmate relations.

4.3.1 ERGM Goodness-of-Fit

Similar to linear regression, a model may or may not fit the data well. With ERGMs, testing the goodness-of-fit is important to understand whether the parameter estimates modeled capture the complexity of the network accurately. To measure goodness-of-fit, after ERGM estimation, a subset of randomly drawn graphs are extracted and, given the specified parameters, these simulations’ parameter statistics are compared with the actual graphs statistics. That is, if indegree is one of the fit statistics, then the average count across the simulated graphs for an indegree of zero, one, two, and so on, is compared with the actual count of indegree of zero, one, two, and so on of the actual network graph. Where the simulation statistics are comparable to the actual statistics, then one can say that the goodness-of-fit for that statistic is strong. The actual comparison is done using $t$-test, with a $p$-value of 0.05 or greater indicating a good fit and a value less than 0.05 as a bad fit.

Because there were 31 networks to estimate, visual depiction of the goodness-of-fit for model parameters was used. The parameters used to assess goodness-of-fit include terms that were explicitly modeled in the ERGM, such as indegree, outdegree, and edgewise shared partners, and those parameter terms not modeled, such as dyadwise shared partners and the triad census. Using both modeled and unmodeled parameters in assessing goodness-of-fit allows one to understand how well the model fit the parameters modeled as well as how accurate the model was at capturing general structure of the network.

In each figure, each point represents the percent of observations with that particular parameter for a village. So, for example, in figure 4.9, most villages had between 15-to-20 percent of children with an indegree of three. Light blue points represent villages with good simulation fit on the parameter, while red points represent a poor fit (as compared to the
actual network observation). Each panel represents one of the three model specifications – structural, cognitive, or GIS. Finally, for clarity, points have been jittered so that there is less overlap; therefore, for no observation was the percentage of observations actually less than zero, there was just a clumping of villages at zero percent.

For indegree (figure 4.9), there was more trouble at the low end of the distribution than the high end, as the number of villages with a poor fit on isolates was about three
(for the GIS model) to five (for the structural model). However, as the indegree rose, the model did a fairly good job of capturing the indegree distribution for the villages.

In terms of outdegree (see figure 4.10), the ERGM seemed to do a better job of capturing the network structure. In all three model specifications, there were only a few villages that had a bad fit. In subsequent analyses (not presented), the villages with poor fits were usually those that estimated, but failed to converge. Given a lack of
convergence, one would expect that the fit of the model might be poorer, given the model could not detect a maximum likelihood. While I opted for a common model to better allow comparisons within the MLM, another approach to deal with the poor fit would be to refine the model for villages with a poor fit and re-estimate to reach convergence.

Figure 4.11. Playmate ERGM Goodness-of-Fit by Estimation Type – Edgewise Shared Partners Distribution

The final modeled parameter to be tested on goodness-of-fit was edgewise shared partners. Again, similarly to the outdegree distribution, the fit is quite good across
villages. Interestingly, while there tended to be significantly more triadic closure than was expected by change (see table 4.6 and figure 4.6), in absolute terms, most villages had very few edgewise shared partners as evidenced by figure 4.11. So while there were few actual edgewise shared partners, controlling for tie configuration, they were a significant part of most villages’ network structure. Again, the outliers tended to be villages that estimated, but failed to converge.

Figure 4.12. Playmate ERGM Goodness-of-Fit by Estimation Type – Dyadwise Shared Partners Distribution
One of the two terms in the goodness-of-fit diagnostics that was not explicitly modeled was dyadwise shared partners. While edgewise shared partners represent the closing of a triangle between three actors, dyadwise shared partners represent multiple two-paths between two actors. That is, if Hank can reach Dana through Gery and through Matt, then Hank has two dyadwise shared partners to Dana – Gery and Matt. One would expect, over time, that the gap between Hank and Dana would close directly, either by Hank sending a tie to Dana (triadic closure) or Dana sending a tie to Hank (cyclic triple).

In figure 4.12, for each model specification, there are almost no dyadwise shared partners in any of the villages. This fits with information on two-paths from table 4.6 and figure 4.6, as two-paths were, in aggregate, found less frequently than would be expected by chance. While the fit on the dyadwise shared partners distribution was decent, it did seem that more than just the non-converged failed to have a good fit.

Given the makeup of the edgewise and dyadwise shared partners results, there seems to be an interesting story. While both structures represent higher-order structural effects, for these villages, it seems there was very little “getting to know someone” through another; there was either connection or not among three actors. That may be a function of the size of the networks in general (fairly small) or the isolation each village has from one another. It may also be a function of the type of network tie modeled (playmates) where the line between playing and not playing for children may be more clear cut than say with friendship evolution. However, this is speculation at best; a longitudinal model would be needed to better understand whether there is selection, influence, or both happening in these networks.

Finally, the triad census was modeled for goodness-of-fit. The triad census – discussed in Holland and Leinhardt (1970) – involves the 16 different configurations of triangles between three nodes in a directed network. These triadic configurations are numbered uniquely; while all are modeled in figure 4.13, ones of importance are those labeled 003, 030T, 030C, 120U, 120D, and 300. In these configurations, 003 represents three nodes with no ties to each other, 030T represents a transitive triad, 030C represents a cyclic triad, 120U and 120D represent mutual ties between two actors with each of those two
actors sending/receiving a tie to a third actor, respectively, and 300 representing mutual
ties between all three actors. These types of configurations tend to represent important
triadic configurations in the literature.

In figure 4.13, the 003 structure tended to fit well and seemed to represent the majority
of observations in villages. This, again, is not surprising given the lack of absolute triadic
activity in these networks in total. For transitive triads (030T), the fit was fairly poor –
about half of the villages had a bad fit; similarly, cyclic triples (030C) and activity (120U) seemed to fit rather poorly. However, popularity (120D) and complete mutual ties (300) seemed to fit relatively well across villages. Given the very low percent of observations for configurations other than isolation (003) across villages, the fit on triad census may not be too important overall.

In addition to goodness-of-fit, after ERGM estimation a series of MCMC diagnostics were performed to determine how well the MCMC method evolved from the starting point. Since the concept of MCMC is to obtain a random sample via stochastic methods, these diagnostics are important in understanding how well that process worked. The diagnostic output and explanations, however, are presented in appendix C.

4.4 Multi-Level Model Estimations

While ERGMs detect the structure and levels of homophily based on ties between actors, they do not relate network characteristics to an individual-level attribute of interest, such as math or language performance. Linear modeling, however, can identify relationships between individual characteristics and an outcome. Therefore, a three-level multi-level model is used to explore how village-, household-, and individual-level attributes affect children’s math and language performance in school. ERGM parameters are included at the village level, relating network-level effects to individual outcomes.

To include ERGM effects in the MLM, the \( t \)-statistics for ERGM terms within each network were extracted and made into a village-level vector of coefficients. Since ERGM terms are incomparable across networks due to the size of the network, the \( t \)-statistic relates a common metric – the parameter estimate divided by the parameter standard error – which is comparable across networks. For clarity, absolute difference (e.g., \( \text{ABSDIFF} \)) terms in ERGMs have had the sign switched on the \( t \)-statistic. As explained in section 4.3, a significantly negative parameter estimate on an absolute difference terms indicates homophily as there is less difference between actors than would be expected by chance. Since the MLM is interested in interpreting homophily, the sign has switched so that interpretation of a positive MLM coefficient for an absolute difference term is for
homophily, not heterophily.

For each of the two outcomes of interest – math performance and language performance – two sets of models were estimated for each of the three ERGM specifications. The first set of models utilized a three-level random intercept MLM, where children were clustered within households within villages. These are tables 4.7 through 4.10. The second set of models utilized a three-level random intercept MLM, but also incorporated random slopes for children’s indegree and outdegree. This allowed for differences between children based on the level of connectedness they had within the playmate network. However, both statistically and substantively, these random-slope models differed very little from the random-intercept models. Therefore, they have been excluded from the results. Finally, the intraclass correlation (ICC) for the various models are presented in table 4.11. The ICC describes the amount of variance in the model explained at the various levels (i.e., village, household, and child).

Tables 4.7 and 4.8 present results for math achievement at the village- and household/individual-levels, respectively. Across all three ERGM specification types (structural, cognitive, and GIS), the treatment indicator for the randomized control trial is significantly positive, indicating that the community-based school program was successful in increasing students’ math performance. The effect is between 0.57 standard deviations for the structural model to 0.4 standard deviations for the GIS model.

While village size had no effect on math achievement, there is mixed evidence about the modal identity for villages. Using a household-level question about how the household self-identified, a modal identity was created for the village. Villages that were primarily comprised of Dari-speaking households or Tajik households performed better in math, but only under the cognitive specification. However, villages with mostly Tajik households actually performed worse in math under the GIS specification. The comparison group under each model is a non-specific “other” identity catch-all. Note, Dari-speakers and ethnic Tajiks comprised the majority of the overall sample for this study.

Network density – or the proportion of ties present divided by the total ties possible – was negative under each specification, but only significant for the cognitive specification.
This indicates that as density of ties increased within the village, children did worse in math, which is interesting. If one thought that greater density meant greater chances for children to learn from one another, then a significantly negative density result is counter-intuitive. However, the result may indicate that as density increases, the ability for influence is traded between a stronger message and the diffusion of the message between actors; this harkens to the structural impact of Latané (1981) and the conceptual model in figure 2.1. Further testing of this theory would be warranted to truly understand the role density of a network has on children’s learning.

The rest of the village-level terms in the MLM were the estimated ERGM parameter t-statistics. For both the structural and cognitive models, there was a significantly negative effect for the edges term. Edges, which measured the number of ties in the network, was significantly negative in most of the ERGM estimations, indicating fewer ties observed than one would expect randomly. Within the MLM then, the significantly negative estimate indicates that the fewer ties in the network, the worse the performance of a child in math. Combined with the density result above, this indicates that there might be a “middle ground” for connections that could benefit children’s learning. Too many ties and density indicates that children’s performance may suffer; likewise, too few ties and the ability of children to learn from one another could be negatively affected.

For the GIS model, there was a significantly positive effect on mutual ties. In this ERGM model, the networks were entrained with distance ties from child-to-child. Therefore, with a significantly positive distance effect (children were more likely to be friends with those living closer to them), then the mutual term could indicate connections mediated by distance. Within the MLM, this translates into having stronger ties (i.e., reciprocity in playmate ties) is indicative of higher math performance.

Moreover, both the twopath and GWOutdegree terms had a significantly negative effect on math performance in the GIS model. Again, the entrainment of the network based on distance may affect the need or quality of extra relationships. Both twopath and GWOutdegree are dyad-dependent terms. In the case of twopath, it is a connection from A to B to C; this precursor to GWESP and cyclic triples indicated that networks with
### Table 4.7. MLM Math Random Intercept Model Results – Village-Level Effects

**Dependent variable:** Math Score (Standardized)

<table>
<thead>
<tr>
<th></th>
<th>Structural</th>
<th>Cognitive</th>
<th>GIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment Village</td>
<td>0.569***</td>
<td>0.522***</td>
<td>0.395***</td>
</tr>
<tr>
<td>(0.085)</td>
<td>(0.089)</td>
<td>(0.094)</td>
<td></td>
</tr>
<tr>
<td>Village Size</td>
<td>–0.0002</td>
<td>–0.001</td>
<td>–0.001</td>
</tr>
<tr>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Mostly Aimaq</td>
<td>0.161</td>
<td>–0.067</td>
<td>–0.120</td>
</tr>
<tr>
<td>(0.103)</td>
<td>(0.086)</td>
<td>(0.135)</td>
<td></td>
</tr>
<tr>
<td>Mostly Dari-Speaking</td>
<td>0.134</td>
<td>0.213*</td>
<td>–0.274</td>
</tr>
<tr>
<td>(0.128)</td>
<td>(0.125)</td>
<td>(0.174)</td>
<td></td>
</tr>
<tr>
<td>Mostly Tajik</td>
<td>–0.055</td>
<td>0.727*</td>
<td>–0.411***</td>
</tr>
<tr>
<td>(0.131)</td>
<td>(0.439)</td>
<td>(0.151)</td>
<td></td>
</tr>
<tr>
<td>Network Density</td>
<td>–2.940</td>
<td>–8.875***</td>
<td>–2.808</td>
</tr>
<tr>
<td>(2.329)</td>
<td>(2.520)</td>
<td>(2.295)</td>
<td></td>
</tr>
<tr>
<td>ERGM Edges</td>
<td>–0.169*</td>
<td>–0.138</td>
<td>–0.147***</td>
</tr>
<tr>
<td>(0.087)</td>
<td>(0.091)</td>
<td>(0.055)</td>
<td></td>
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<tr>
<td>ERGM Mutual</td>
<td>0.024</td>
<td>–0.011</td>
<td>0.126***</td>
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<tr>
<td>(0.025)</td>
<td>(0.031)</td>
<td>(0.043)</td>
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<tr>
<td>ERGM Twopath</td>
<td>0.026</td>
<td>–0.028</td>
<td>–0.075**</td>
</tr>
<tr>
<td>(0.026)</td>
<td>(0.037)</td>
<td>(0.036)</td>
<td></td>
</tr>
<tr>
<td>ERGM Geo.-Weighted Outdegree</td>
<td>0.055</td>
<td>–0.071*</td>
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</tr>
<tr>
<td>(0.043)</td>
<td>(0.038)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERGM Geo.-Weighted Edgewise Shared Partners</td>
<td>–0.080**</td>
<td>–0.107*</td>
<td>–0.052**</td>
</tr>
<tr>
<td>(0.034)</td>
<td>(0.055)</td>
<td>(0.052)</td>
<td></td>
</tr>
<tr>
<td>ERGM Gender Homophily</td>
<td>–0.282***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.074)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERGM Math Homophily</td>
<td>0.176***</td>
<td>0.059</td>
<td></td>
</tr>
<tr>
<td>(0.063)</td>
<td>(0.038)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERGM Language Homophily</td>
<td>0.053</td>
<td>0.001</td>
<td></td>
</tr>
<tr>
<td>(0.037)</td>
<td>(0.041)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERGM Near School Proximity</td>
<td>–0.088**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.042)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERGM Distance (Mutual Ties)</td>
<td>0.156**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>(0.074)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Observations:** 1,342, 1,178, 1,298

**Log Likelihood:** –1,433.554, –1,252.017, –1,384.954

**Akaiek Inf. Crit.:** 2,935.108, 2,580.034, 2,847.909

**Bayesian Inf. Crit.:** 3,111.973, 2,772.754, 3,049.483

*Note:* *p<0.1; **p<0.05; ***p<0.01
open triads negatively affected children’s performance in math. With GWOOutdegree, the
ERGM terms captures propensity of actors to send ties, also termed activity. As activity
increases in the network, this has a negative affect on performance. Similar to the density
parameter, these seem to be a middle level of ties or activity that seem to be indicative
of math performance.

Geometrically-weighted edgewise shared partners show a significantly negative effect
on math performance across all three model specifications. The GWESP ERGM term
captures the propensity towards triadic closure. In the MLM, this would indicate that
higher levels of triadic closure in a network can be detrimental to math performance,
which follows from the twopath result discussed above.

The cognitive and GIS models include a series of compositional parameters, such as
gender homophily, math/language performance homophily, physical proximity to school,
and physical distance from playmates. For the cognitive model, gender homophily was
a significant term. Gender homophily, or the propensity to be tied to those of the same
gender, was strong across all networks. Boys tended to play with other boys and girls
tended to play with girls. However, within the MLM, it seems that the higher the level of
gender homophily amongst children within the village, the lower the math performance.
This could be indicative of benefits to having cross-gender playmates, though this should
be interpreted cautiously and is worth more study.

While language homophily was insignificant in both the cognitive and GIS specifica-
tions of the MLM, math homophily was significantly positive in the cognitive model.
This positive homophily terms means that for networks where children with similar math
ability were more likely to be playmates with one another, their math performance im-
proved. In other words, being playmates with someone of a similar math ability is helpful
in one’s own math performance. The mechanism may be an ability to feel comfortable
with others of the same ability or a chance to work through math at a similar pace or
ability. However, as with gender homophily, this finding should be further studied and
confirmed with more definitive work.

There was a significantly negative effect of increasing the physical distance from school
Table 4.8. MLM Math Random Intercept Model Results – Household- and Individual-Level Effects

<table>
<thead>
<tr>
<th></th>
<th>Math Score (Standardized)</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Structural</td>
<td>Cognitive</td>
<td>GIS</td>
</tr>
<tr>
<td>Years in Village</td>
<td>−0.003**</td>
<td>−0.003*</td>
<td>−0.003**</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>Aimaq Household (HH)</td>
<td>−0.004</td>
<td>−0.058</td>
<td>−0.002</td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td>(0.066)</td>
<td>(0.065)</td>
</tr>
<tr>
<td>Dari-Speaking HH</td>
<td>0.086</td>
<td>0.052</td>
<td>0.083</td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.071)</td>
<td>(0.069)</td>
</tr>
<tr>
<td>Tajik HH</td>
<td>0.126*</td>
<td>0.115*</td>
<td>0.106</td>
</tr>
<tr>
<td></td>
<td>(0.065)</td>
<td>(0.070)</td>
<td>(0.067)</td>
</tr>
<tr>
<td>Main Occupation: Farmer</td>
<td>−0.008</td>
<td>−0.017</td>
<td>−0.008</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.054)</td>
<td>(0.052)</td>
</tr>
<tr>
<td>Head of Household (HoH) Years of Education</td>
<td>0.013**</td>
<td>0.016**</td>
<td>0.013**</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Number in HH</td>
<td>0.008</td>
<td>0.008</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Irrigated Land (Jeribs)</td>
<td>0.004</td>
<td>0.005</td>
<td>0.005</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Age Boy Should Stop Education</td>
<td>−0.005</td>
<td>−0.010</td>
<td>−0.003</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.007)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Age Girl Should Stop Education</td>
<td>−0.003</td>
<td>0.002</td>
<td>−0.006</td>
</tr>
<tr>
<td></td>
<td>(0.008)</td>
<td>(0.009)</td>
<td>(0.008)</td>
</tr>
<tr>
<td>Beating Child Okay</td>
<td>−0.054</td>
<td>−0.046</td>
<td>−0.068</td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td>(0.057)</td>
<td>(0.054)</td>
</tr>
<tr>
<td>Neighbors are Important</td>
<td>−0.099</td>
<td>−0.087</td>
<td>−0.118*</td>
</tr>
<tr>
<td></td>
<td>(0.071)</td>
<td>(0.079)</td>
<td>(0.072)</td>
</tr>
<tr>
<td>Female</td>
<td>−0.384***</td>
<td>−0.371***</td>
<td>−0.386***</td>
</tr>
<tr>
<td></td>
<td>(0.040)</td>
<td>(0.043)</td>
<td>(0.041)</td>
</tr>
<tr>
<td>Child’s Age</td>
<td>0.182***</td>
<td>0.181***</td>
<td>0.187***</td>
</tr>
<tr>
<td></td>
<td>(0.014)</td>
<td>(0.015)</td>
<td>(0.014)</td>
</tr>
<tr>
<td>Child’s Years of Education</td>
<td>0.183***</td>
<td>0.172***</td>
<td>0.175***</td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.024)</td>
<td>(0.022)</td>
</tr>
<tr>
<td>Child Works</td>
<td>0.129</td>
<td>0.149</td>
<td>0.141</td>
</tr>
<tr>
<td></td>
<td>(0.101)</td>
<td>(0.109)</td>
<td>(0.101)</td>
</tr>
<tr>
<td>Number Days School Attended Last Two Weeks</td>
<td>0.071***</td>
<td>0.078***</td>
<td>0.071***</td>
</tr>
<tr>
<td></td>
<td>(0.009)</td>
<td>(0.009)</td>
<td>(0.009)</td>
</tr>
<tr>
<td>Indegree</td>
<td>0.070***</td>
<td>0.071***</td>
<td>0.071***</td>
</tr>
<tr>
<td></td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.011)</td>
</tr>
<tr>
<td>Outdegree</td>
<td>0.051***</td>
<td>0.047***</td>
<td>0.049***</td>
</tr>
<tr>
<td></td>
<td>(0.015)</td>
<td>(0.016)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Brokerage</td>
<td>−0.011*</td>
<td>−0.010*</td>
<td>−0.013**</td>
</tr>
<tr>
<td></td>
<td>(0.006)</td>
<td>(0.006)</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Constant</td>
<td>−2.009***</td>
<td>−0.826**</td>
<td>−2.028***</td>
</tr>
<tr>
<td></td>
<td>(0.363)</td>
<td>(0.409)</td>
<td>(0.388)</td>
</tr>
</tbody>
</table>

| Observations | 1,342 | 1,178 | 1,298 |
| Log Likelihood  | −1,433.554 | −1,252.017 | −1,384.954 |
| Akaike Inf. Crit. | 2,935.108 | 2,580.034 | 2,847.909 |
| Bayesian Inf. Crit. | 3,111.973 | 2,772.754 | 3,049.483 |

Note: *p<0.1; **p<0.05; ***p<0.01
on math performance. This follows from Burde and Linden (2012), which indicated that children’s attendance dropped precipitously as distance from the school increased. Finally, at the village level, having reciprocated ties with those physically close to one another was indicative of greater math performance. Being playmates with those that are proximally close with another may – like having friends of like ability – allow for peer effects to happen naturally with respect to achievement. This should be more formally tested within a longitudinal network model to separately identify any selection or influence effects of playmate ties.

Table 4.8 presents household- and individual-level effects. At the household level, there are very few significant factors in children’s math achievement. Having lived more years in the village indicated significantly worse math performance; however the effect size is quite small and likely of little practical significance. Being ethnically Tajik – as compared to a non-specific “other” identity – was indicative of higher math performance under both the structural and cognitive specifications.

Unsurprisingly, the head of household having more education was indicative of greater child math performance. This could indicate social norms within the household for education or simply an ability to assist children with their lessons. Finally, for the GIS model specification, there was a negative effect for neighbor importance. As the household belief in neighbors increased, math performance of the child decreased. Without further evidence of neighbor norms, it is difficult to interpret this effect. If neighbors, for example, believe that education was unimportant, this effect could represent a type of social conformity; however, there could be alternate explanations as well.

At the child level, most effects were significant and in expected directions. As found in Burde and Linden (2012, 2013), females performed significantly worse in math than boys across model specifications, while older children performed significantly better. The years of education a child had was a significantly positive indicator of performance as was attendance at school; greater attendance translated into better math performance.

Also at the child level are individual network measures of indegree (number of nominations a child received), outdegree (number of nominations a child made), and brokerage.
Table 4.9. MLM Language Random Intercept Model Results – Village-Level Effects

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Language Score (Standardized)</th>
<th>Structural</th>
<th>Cognitive</th>
<th>GIS</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment Village</td>
<td>0.516***</td>
<td>0.374***</td>
<td>0.240***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.068)</td>
<td>(0.090)</td>
<td>(0.077)</td>
<td></td>
</tr>
<tr>
<td>Village Size</td>
<td>−0.0004</td>
<td>−0.002*</td>
<td>−0.002***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.001)</td>
<td>(0.001)</td>
<td></td>
</tr>
<tr>
<td>Mostly Aimaq</td>
<td>0.081</td>
<td>−0.114</td>
<td>−0.263**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.085)</td>
<td>(0.087)</td>
<td>(0.114)</td>
<td></td>
</tr>
<tr>
<td>Mostly Dari-Speaking</td>
<td>0.070</td>
<td>0.114</td>
<td>−0.470***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.107)</td>
<td>(0.127)</td>
<td>(0.149)</td>
<td></td>
</tr>
<tr>
<td>Mostly Tajik</td>
<td>0.068</td>
<td>0.918**</td>
<td>−0.232*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.445)</td>
<td>(0.119)</td>
<td></td>
</tr>
<tr>
<td>Network Density</td>
<td>−3.114</td>
<td>−6.977***</td>
<td>−2.228</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(2.024)</td>
<td>(2.550)</td>
<td>(2.000)</td>
<td></td>
</tr>
<tr>
<td>ERGM Edges</td>
<td>−0.226***</td>
<td>−0.261***</td>
<td>−0.086*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.072)</td>
<td>(0.092)</td>
<td>(0.045)</td>
<td></td>
</tr>
<tr>
<td>ERGM Mutual</td>
<td>0.027</td>
<td>0.005</td>
<td>0.082**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.020)</td>
<td>(0.032)</td>
<td>(0.035)</td>
<td></td>
</tr>
<tr>
<td>ERGM TwoPath</td>
<td>−0.009</td>
<td>−0.099***</td>
<td>−0.132***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.022)</td>
<td>(0.038)</td>
<td>(0.029)</td>
<td></td>
</tr>
<tr>
<td>ERGM Geo.-Weighted Outdegree</td>
<td>−0.037</td>
<td>−0.119***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.044)</td>
<td>(0.032)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERGM Geo.-Weighted Edgewise Shared Partners</td>
<td>−0.119***</td>
<td>−0.155***</td>
<td>−0.023</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.028)</td>
<td>(0.056)</td>
<td>(0.018)</td>
<td></td>
</tr>
<tr>
<td>ERGM Gender Homophily</td>
<td>−0.206***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.075)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERGM Math Homophily</td>
<td>0.154**</td>
<td>0.073**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td>(0.031)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERGM Language Homophily</td>
<td>0.079**</td>
<td>0.055</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.034)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ERGM Near School Proximity</td>
<td>−0.038</td>
<td></td>
<td>−0.038</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td></td>
<td>(0.036)</td>
<td></td>
</tr>
<tr>
<td>ERGM Distance (Mutual Ties)</td>
<td>0.071</td>
<td></td>
<td>0.071</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.061)</td>
<td></td>
<td>(0.061)</td>
<td></td>
</tr>
</tbody>
</table>

Note: *p<0.1; **p<0.05; ***p<0.01

Observations 1,342 1,178 1,298
Log Likelihood −1,473.454 −1,288.053 −1,415.702
Akaike Inf. Crit. 3,014,909 2,652,106 2,909,405
Bayesian Inf. Crit. 3,191,774 2,844,826 3,110,979
Brokerage is a specific network term to denote the role(s) that an actor plays inside and outside their specific subgroup of the network. In Gould and Fernandez (1989), authors indicated actors could be coordinators and mediate contact between members of their group; they could be itinerant brokers and mediate contact between two members of a different group; they could be representatives and mediate information from an out-group to an in-group member; they could be a gatekeeper, which mediated information from an in-group member to an out-group member; or, they could be a liaison, which mediated information from a member of one out-group to a member of a different out-group. In these analyses, brokerage is concerned with how a child mediates contact between other in-group members (i.e., a coordinator role). In this way, a higher brokerage score represents a child that sits between other group members and helps mediate contact. In essence, these children act as bridges of information to others.

Across all models, higher indegree and outdegree scores were indicative of better math performance. So, sociality – as represented by popularity (indegree) and activity (outdegree) – showed a significant association with math performance. However, serving as a bridge between group members (brokerage) indicated poorer math performance. This may be a function of focusing on others rather than themselves, though other explanations are plausible as well, such as less important in-group members serve more subservient roles in the group, like the go-between. Moreover, while significant, the effect size for brokerage is quite small, indicating practical significance may be lacking.

Tables 4.9 and 4.10 present results for the language achievement outcome. As with math, being in a treatment village was significantly positive, indicating the CBS program was effective at increasing math, as well as language, achievement. Being from a larger village was indicative of worse language performance, though the effect size was quite small and only holds for the cognitive and GIS model specifications. Compared to the non-specific “other” identity reference group, villages mostly comprised of Dari-speakers seemed to do worse in language performance in the GIS model. This is surprising, since the language tested across villages was Dari. Presumably, self-identified Dari-speakers would have an advantage in language, but that was not the case. For villages primarily
comprised of Tajiks, there was mixed evidence on language performance. Under the cognitive model, Tajik villages performed significantly better than the reference group, but significantly worse than the reference group under the GIS specification.

As with math achievement, there was a significantly negative effect on density. Controlling for all else, children in villages where density was higher did worse in language achievement than others. Likewise, edges, twopath, GWOutdegree, and GWESP were all significantly negative for various model specifications for the language outcome. However, for the GIS specification on the mutual ERGM term, there was a significantly positive association.

Compositionally, there was a negative gender homophily term in the cognitive model for language (as it was for math), indicating that children in villages where more playmate relationships were between same-gender children did worse in language. It is important to note though that across villages, gender homophily was very high, which means the gender homophily effect must be interpreted with caution. There were stronger performance homophily effects around the language outcome than with math. In both the cognitive and GIS model specifications, math homophily was significantly positive with respect to individual language performance.

Moreover, there was a positive effect in the cognitive specification for language homophily, an effect unseen with the math outcome. This indicates that in villages where children were more likely to be playmates with others of a similar language ability, there was a reinforcing effect on individual performance in language. Reciprocated peer learning may be the mechanism, but it would be advantageous to test this effect in a longitudinal network model to tease apart selection and influence effects. For language performance, there were no distance-related effects that were significant.

At the household-level (table 4.10, years the household had lived in the village again had a significantly negative association with language performance. However, there were no identity-related effects for language, unlike with math performance. The head of household having more education was again predictive of better language achievement, as was having more irrigated land for the cognitive and GIS specifications. Households
### Table 4.10. MLM Language Random Intercept Model Results – Household- and Individual-Level Effects

<table>
<thead>
<tr>
<th>Dependent variable:</th>
<th>Language Score (Standardized)</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Structural</td>
<td>Cognitive</td>
</tr>
<tr>
<td>Years in Village</td>
<td>–0.004***</td>
<td>–0.004**</td>
</tr>
<tr>
<td>Aimaq Household (HH)</td>
<td>0.033 0.061 0.051</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.001) (0.002) (0.001)</td>
<td></td>
</tr>
<tr>
<td>Dari-Speaking HH</td>
<td>0.049 0.051 0.069</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009) (0.072) (0.070)</td>
<td></td>
</tr>
<tr>
<td>Tajik HH</td>
<td>0.082 0.105 0.050</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.067) (0.071) (0.067)</td>
<td></td>
</tr>
<tr>
<td>Main Occupation: Farmer</td>
<td>–0.001 0.010 0.005</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.052) (0.055) (0.052)</td>
<td></td>
</tr>
<tr>
<td>Head of Household (HoH) Years of Education</td>
<td>0.028*** 0.028*** 0.028***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007) (0.007) (0.007)</td>
<td></td>
</tr>
<tr>
<td>Number in HH</td>
<td>0.008 0.012* 0.009</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.007) (0.007) (0.007)</td>
<td></td>
</tr>
<tr>
<td>Irrigated Land (Jeribs)</td>
<td>0.016 0.021** 0.022**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.010) (0.010) (0.010)</td>
<td></td>
</tr>
<tr>
<td>Age Boy Should Stop Education</td>
<td>0.003 –0.005 0.002</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006) (0.007) (0.007)</td>
<td></td>
</tr>
<tr>
<td>Age Girl Should Stop Education</td>
<td>–0.007 –0.003 –0.009</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.008) (0.009) (0.008)</td>
<td></td>
</tr>
<tr>
<td>Beating Child Okay</td>
<td>–0.108** –0.106* –0.117***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.054) (0.058) (0.054)</td>
<td></td>
</tr>
<tr>
<td>Neighbors are Important</td>
<td>–0.019 –0.034 –0.055</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.072) (0.080) (0.072)</td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>–0.294*** –0.295*** –0.293***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.041) (0.044) (0.042)</td>
<td></td>
</tr>
<tr>
<td>Child’s Age</td>
<td>0.147*** 0.132*** 0.147***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.014) (0.015) (0.014)</td>
<td></td>
</tr>
<tr>
<td>Child’s Years of Education</td>
<td>0.263*** 0.272*** 0.254***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.023) (0.024) (0.023)</td>
<td></td>
</tr>
<tr>
<td>Child Works</td>
<td>0.239** 0.226** 0.258**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.104) (0.113) (0.104)</td>
<td></td>
</tr>
<tr>
<td>Number Days School Attended Last Two Weeks</td>
<td>0.040*** 0.038*** 0.040***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.009) (0.010) (0.009)</td>
<td></td>
</tr>
<tr>
<td>Indegree</td>
<td>0.075*** 0.066*** 0.076***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.011) (0.012) (0.011)</td>
<td></td>
</tr>
<tr>
<td>Outdegree</td>
<td>0.058*** 0.053*** 0.060***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.016) (0.017) (0.016)</td>
<td></td>
</tr>
<tr>
<td>Brokerage</td>
<td>–0.010* –0.003 –0.012*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.006) (0.006) (0.007)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>–1.983*** –1.118*** –1.967***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.331) (0.415) (0.350)</td>
<td></td>
</tr>
</tbody>
</table>

| Observations | 1,342 1,178 1,298 |
| Log Likelihood | –1,473.454 –1,288.053 –1,415.702 |
| Akaike Inf. Crit. | 3,014.909 2,652.106 2,909.405 |
| Bayesian Inf. Crit. | 3,191.774 2,844.826 3,110.979 |

Note: *p<0.1; **p<0.05; ***p<0.01
were primarily engaged in agriculture and having more irrigated land was an indication of greater socio-economic status. Interestingly, a household’s belief in corporal punishment was related to language achievement. This was not seen with the math outcome. In households that believed beating a child was an acceptable form of punishment, children did significantly worse. While this is a plausible association, it is interesting it did not come about in math performance as well.

Table 4.11. ICC for Math/Language Random Intercept Models

<table>
<thead>
<tr>
<th></th>
<th>Math Models</th>
<th></th>
<th>Language Models</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Structural</td>
<td>Cognitive</td>
<td>GIS</td>
<td>Structural</td>
</tr>
<tr>
<td>Village</td>
<td>0.036</td>
<td>0.000</td>
<td>0.014</td>
<td>0.012</td>
</tr>
<tr>
<td>HH</td>
<td>0.144</td>
<td>0.149</td>
<td>0.144</td>
<td>0.126</td>
</tr>
<tr>
<td>Child</td>
<td>0.821</td>
<td>0.851</td>
<td>0.841</td>
<td>0.862</td>
</tr>
</tbody>
</table>

Individually, results between the math and language outcomes are quite similar. Females did significantly worse than males, while older children did significantly better. More years of education and better attendance at school were also predictive of better language achievement. However, if the child worked, the child tended to do significantly better in language. This differs from the math outcome, where there were no associations between work and math performance. If children are working with adults, it could be that their language skills are adapting more quickly, but this is just a hypothesis and unproven. Again, children displaying more sociality (popularity and activity in nominations) did significantly better in language achievement across all models; effects for brokerage, however, were less consistent than with the math outcome.

Finally, in table 4.11, the intraclass correlations for the various levels of both the math and language outcomes are presented. The ICC displays how much of the variation around the outcome is explained at the various levels (i.e., village-, household-, and individual-levels). For both math and language models, unsurprisingly, the majority of the variance is explained by individual-level variables (around 82 to 89 percent, depending on the model). Between 11 and 15 percent of variation was attributable to the household level, whereas only 0 to 3.5 percent of variation was due to village-level factors. In essence, while
the nesting order of children within households within villages matters to appropriately model effects, the strongest indicators of children’s academic performance are driven by their personal characteristics and attributes.

4.5 Results Summary

These analyses started with demographic comparisons between treatment and control groups, moved on to look specifically at isolated versus non-isolated (in a network sense) children, while then describing the basic network structure of the 31 villages in aggregate. Next, exponential random graph models were run independently on each village; a common model was fit across villages. Both the t-statistic parameters and the goodness-of-fit were studied in aggregate. Next, the ERGM t-statistics were used as village-level parameter values in a multi-level model that nested children within households within villages. A random-intercept model was fitted, along with a random-slope model, but there was little substantive difference between the two. Finally, the intraclass correlations of the MLMs were assessed to determine that the majority of variance was explained at the child-level.

The household- and child-level demographics between treatment and control groups were fairly well-balanced. This is to be expected given successful randomization. The treatment group showed stronger academic performance, but this was due to the treatment; there was no underlying baseline measure to assess the difference between treatment and control on these outcomes. Moreover, the treatment group seemed better off economically, but this was subsequently controlled for in the MLMs.

A second demographic analysis was conducted of network isolates versus non-isolates. An isolate, in a network sense, is a person with no incoming or outgoing ties. They tended to be different from others in the network on various characteristics. Isolates did significantly worse in math and language performance, tended to be younger, and in general, attended school less often. However, there were few differences between the treatment and control isolates, indicating isolates performance is orthogonal to the outcome, not caused by it.

Network structural measures – the building blocks of how a network operates – were
summarized in aggregate. There were few differences between treatment and control villages on these measures. Next, a common ERGM was fit for each village. The majority of ERGMs both estimated and converged. Being able to fit a common model meant that the ERGM $t$-statistics could be used in predicting individual-level outcomes. To ensure that statistics from the ERGMs were reliable, a series of goodness-of-fit diagnostics were used. For the most part, networks performed well; outliers with poor performance on a particular parameter were often networks that failed to converge.

Finally, MLMs utilizing the network parameters at the village level showed village-, household-, and child-level effects. However, child-level effects predominated and accounted for most of the variation in children’s math and language outcomes. Interestingly, many of the network structural parameters were negative; given the novelty of using ERGM $t$-statistics in linear modeling, the interpretation and meaning of these statistics should be given special attention. For both math and language, gender and performance (math/language) homophily terms had a significant influence on children’s academic achievement; for math, distance to one’s friends was also important. The following chapter discusses the importance of these results for development practitioners.
Chapter 5

Discussion

The use of social network information in the realm of development interventions is novel. Few programs or organizations have incorporated network information into their work, though based on the results in chapter 4, development organizations and program managers should consider explicitly using networks to strengthen interventions through better identification of those lagging behind others, utilizing the types of connections individuals maintain to strengthen and create new relationships, and leveraging joint behavior between individuals that are tied to one another to improve individual outcomes. The end result may be a sustainable mechanism for the intervention, which can be critical when resource constraints, security, or other factors impede an organization’s ability to continue delivering the intervention.

For international development, social networks may help answer three key questions. First, what do these networks reveal about a target population that is otherwise unknown; second, how does the structure of the network affect the ability of the intervention to spread across the network; and third, how can an organization or program manager target specific people within the network? This chapter explores these three questions for organizations seeking to improve their programming by utilizing existing social networks at the local level, using the results of chapter 4 as reference.
5.1 Knowledge from Networks

Networks, in general, reveal a wealth of relational information about people. In the children’s networks discussed earlier, there were a few clear observations about the network. First, playmate connections were almost twice as many as friendship connections. That means, on average, children played with two times as many children as they considered their friend, indicating a greater series of pathways to any particular child through playmates than through friends. If one was concerned with reaching children, then utilizing playmate connections might be key. For example, if an organization was concerned with spreading the word about a new school-based program in these villages, the program manager might tell children at the school to “...tell your playmates about our new program and encourage them to come.” By directing children to discuss information with their playmates, a program manager might reach more children than if they mentioned friends.

What else could a program manager do? The program manager could expand the community-based school program to include more unstructured time for children to interact during the day. This could give children an opportunity to broaden their playmate connections at school. The CBS program was not structured to include unstructured time during the day; however, this may be the only chance that children have to interact with other children that do not live close to them (relying on the finding that children tended to be friends with those that lived near them). Building additional playmate ties could have a positive effect if, for example, the school needed to close temporarily. Children’s playmate ties could potentially insulate against knowledge loss.

Second, networks revealed important information about isolated children. Isolates are interesting from both a network and individual perspective. Isolates cannot receive messages transmitted indirectly; moreover, they are often different from others in the network, as was the case with the playmate networks studied here. Isolated children tended to perform worse than non-isolates in math and language, they tended to be younger, and they also tended to attend school less frequently than non-isolates. In short, isolates in this specific situation represented some of the harder cases for a program manager or organization to impact with the intervention.
Characteristics of isolates will differ by context. For example, if one is looking at a farming network, isolated farmers may be less experienced in farming, poorer, or from a marginalized group. Utilizing a social network to identify particular characteristics of isolates is the first step in crafting solutions to reach out to them and either integrate them into the network or develop alternative mechanisms to ensure their success in the program as well. If one thinks about a typical development program, if the intervention is well-designed, then the first years are likely to show strong success. Those participating in the beginning stages of the intervention are likely motivated to succeed or have a high level of innate ability. However, isolates may hesitate to join the intervention or perform poorly within the intervention. As an organization tries to increase isolates’ success, the program may be nearing completion or lacking resources (i.e., decreased evaluation resources, either internal or external to the program) to identify exactly who is failing. An early network collection could identify “risk” factors of isolates and help program managers identify solutions earlier to those struggling to succeed under the intervention.

Third, measuring the social network provides helpful planning information. The networks studied for this manuscript were sparsely connected (about 5 percent of possible connections were present in the playmate network; about half that in the friendship networks) and decentralized (there were few children in the network that maintained ties to many other children). In other words, there were very few connections within the network and those connections were spread across the entire network, not clustered around specific individuals. This means a program manager knows two things – an approach to “spread the word” will likely be difficult. It may succeed, but it will be slower than if the network were more dense; the scarcity of connections will not allow information to travel quickly. However, the decentralization of the network also means that, with the right strategy, messages can penetrate various parts of the network; information does not simply flow to or from a few individuals. Careful consideration should be taken with whom the manager seeds any message to transmit across the network; the person should be connected to others, but connected to others that can quickly transmit the message to others in the network.
5.2 Network Structure

Network structure involves an intricate mix of simple and complex structures. Ties between people are the basis for any type of structure found in a network. However, the combination of these ties from actor-to-actor-to-actor creates more complex relationships. In the children’s playmate networks in Afghanistan, the first structural realization was that many ties in the network were reciprocated. In fact, while there were few ties in the network overall, a significant number were reciprocated from child-to-child.

Important for network structure is the stronger conduit for potential influence between children caused by reciprocated ties. For example, if Hank nominates Dana as a friend, then Hank shows his affinity for Dana’s friendship; however, Dana may think Hank is not that important of a friend. Therefore, Dana may be unlikely to listen to Hank if he has something to say; however, if Dana’s friendship is mutual with Hank, then there is the possibility of influence from either Hank or Dana to the other. Reciprocity, therefore, opens up the possibility for stronger peer influence mechanisms.

In the networks studied, there was a clear signal that children’s playmate ties were a two-way conduit for information or influence exchange. For a program manager, this is valuable – it provides evidence of how information or an intervention might diffuse through the network. That is, if the program manager wants to develop strong norms around school attendance, spread the message that doing well in school is important, or induce peer learning, then having reciprocated ties means that children not only hear the message from their teacher via the program manager, but also from their peer relations. Reciprocated ties therefore allow both children in the pair to spread and assimilate the message to and from others.

While reciprocity indicates a more complex network structure than a random assortment of ties, there was evidence these networks were fairly simple in structure. Beyond a dyad (two actors), triads (three actors) are important to network structure. The precursor to generalized exchange, for example, is simply the connection of three actors in some way. Triads can be grouped in a multitude of ways. There can be transitive closure, which would represent “a friend of a friend is a friend,” or it can represent some type of hierarchy.
Each is important in their own right and have implications for an organization or program manager looking to utilize network information in strengthening programming.

Two-paths, or a connection from Hank to Dana and from Dana to Gery, were rare in these networks. Two-paths are important for understanding hierarchy (or lack thereof) in networks. If the two-path closes from Gery to Hank, then the cyclic triple indicates there is generalized exchange; that is, no one person in the triad is more important than the other. However, if the triad closes from Hank to Gery that transitive triad indicates there is stronger hierarchy within the triad. That is, Hank views both Dana and Gery as people of importance to him, but that relationship is not reciprocated back to Hank by either Dana or Gery. Therefore, Dana and Gery likely hold sway over Hank in some manner. In the context of school, it may be that Dana and Gery have some expertise that Hank views as desirable and therefore, Dana and Gery maintain higher stature in the local hierarchy than Hank. Maybe Hank is younger and this expertise-seeking is to learn from either Dana or Gery. These local power dynamics are useful to understand, especially in an area like Afghanistan, where knowledge is often difficult to obtain.

Both hierarchy and generalized exchange could be useful to leverage, depending on a program manager’s goals. If the intention of an educational program, for example, was to encourage greater peer exchange for learning, then understanding how to close two-paths into cyclic triples might be relevant. This might be appropriate for younger children who are all at the same level. They could reinforce learning in a structured, non-hierarchical way.

However, if classes were large with mixed ages/levels of students, then a hierarchy in triads may be more appropriate. In Afghanistan, for example, violence had severely disrupted education delivery; children who had traditionally aged out of lower educational grades needed to catch up. Helping these children who were older identify and work through peers their own age that they maintained ties to (as opposed to those with whom they had ties at a similar academic level, but who may be significantly younger) may be one example of how instilling limited local hierarchy in triads may be advantageous. It would rely on the natural formation of ties between children, but also work through a
manipulation of potential tie structure.

For the few triangles that did exist in networks, many of them displayed transitive closure, indicating “a friend of a friend was a friend.” Given the strong, mutual ties between actors, closing a triad relies on the referral of “trusted agents” such as existing mutual contacts. Therefore, to create ties within the network, a more structured approach to tie formation may be needed beyond creating the conditions for tie formation, as suggested above with the introduction of playtime into the academic day. An organization may consider grouping students – enough with connections to each other, but with open triads still – so that over time, both the increased opportunity to create ties (structured playtime) and the purposeful grouping of children (instilling enough trusted agents) can induce triadic effects.

Why though, is triadic closure important? First, developing one’s social network is a natural tendency. Rarely do people go through life with independent mutual dyadic relationships. As triads form and develop, they become interconnected and form subgroups (i.e., a tight group of friends) and components (i.e., a larger group of connected, but distinct, individuals, like children in the same grade at school) that comprise the meta-structure of social networks. Second, in a context like education, triads provide an extra resource for help or influence or both – a person within a triad can help others with their academics, or, if not in school currently, can be influenced to start attending.

5.3 Network Targeting

In addition to network structural effects, there were strong compositional effects that had bearing on outcomes of interest. Most playmate ties were within the same sex. In fact, in five of 31 villages, the separation was absolute – there were no cross-gender playmate ties. This raises interesting points for interventions and organizations that do not explicitly take gender into account when planning their programs. Outreach to individuals\(^1\) might need different strategies to enroll individuals of different genders. Relying on a typical “opinion leader” approach of working through those thought to be influential in the network will

\(^1\)In this case, parents, not the children themselves, likely made the decision on whether the child attended school; therefore, the following point may be more applicable in a different context.
only work if opinion leaders of both genders are utilized. Even with opinion leaders of both genders, the approach taken for each subset may need to differ to reach maximum effect; that is, the emphasis or context of the message may need to differ based on gender.

Another interesting effect regarding gender was villages with stronger within-gender ties (also called homophily, or the tendency towards sameness) was negatively associated with children’s educational outcomes. Since all villages showed strong gender homophily in ties, this finding should be interpreted with caution. The answer is likely not “induce more cross-gender ties” to help increase performance; it is probably more nuanced. The ties and relationships children had with each other were quite strong (see discussion above) so while there is opportunity for peers to affect each other’s learning they may quickly exhaust these existing ties as sources of knowledge; inducing ties across gender may provide access to a greater variety of knowledge or a different way of thinking about particular topics. However, this should be done with great care, given the cultural context of Afghanistan. For a program manager, this is certainly an area to take one’s time to craft a strategy.

Besides gender homophily’s effect on individual math and language performance, homophily in math and language performance at the village level was positively associated with individual-level outcomes. Performance (math, language) homophily at the village-level indicated children tended to have ties to others that performed at a similar level to themselves; note, this could be high performers associated with other high performers or low performers associated with low performers. For math especially, performance homophily was pronounced. The natural grouping by performance level led to significantly increased performance at the individual level. For a program manager, this might suggest setting up the academic program such that students of similar ability work together frequently. This could be combined with the suggestion of grouping to induce triadic closure. There is evidence that grouping based on ability will help individual-level outcomes and it could induce greater, and more complex, tie formation for children. By targeting similarly performing children, a program manager may be able to help boost performance with a low-cost, easily-implemented change to the intervention.

Often, spreading information across a network is important; to better understand how
information may spread, both visual and analytic results could be used. Based on the network visualizations in appendix A, within most villages, there seemed to be at least a couple of components, which means at the very least, individuals from each of those components need to be identified as starting points for any message. The strategy could be as simple as seeding the message with various individuals in the network. Since the number of connections in the networks was low, it may be better to seed messages with those that sit strategically on the pathway to others; these “bridges” can help ensure that even within a component, a message has the ability to reach all individuals. As discussed above, special care needs to be taken with isolates; in the playmate and friendship networks, isolates accounted for 4.6 and 13.3 percent of individuals on average within networks. Working with bridging agents in components and focusing on isolates may prove to be more effective than just working through outreach workers within the village, who are likely to reach popular members of the network, but information may not flow from those people to others (i.e., the person is “popular,” having a high indegree, but does not display much “activity,” or sending ties – their outdegree). In other words, if an organization or program manager does not have the ability to change the network structurally, understanding the network and identifying an appropriate strategy can still satisfy goals of information exchange.

Results indicate that higher indegree and outdegree scores were associated with increased math and language performance. So, a program manager, in lieu of information on the network, might seed information with those that are doing best in school. This is less efficient than understanding the network as a whole and seeding information with appropriate actors, but it would likely help in a pinch.

Finally, considering the age of the children, these networks were still at an early stage of evolution. Very few of the building blocks for more complex structures associated with networks (like twopaths) were present in the networks, which meant there was little in the way of triadic effects. Working to encourage these more complex structures through some of the methods listed above (increased opportunity to form ties, grouping of similarly-abled and tangentially-connected peers) can also be used to create targeting approaches. These may be especially acute for isolates; by working to build them into the structure
of the network and removing them from the periphery, they can then be reached through traditional targeting means within networks via opinion leaders or bridging agents. This is building the sustainability of the network and intervention. As the network strengthens, it has the ability to sustain the intervention during its execution (e.g., if the teacher leaves/dies, students can continue to learn from one another) or after the end of the intervention (e.g., village-level norms around education that encourage the community to continue the school even without programmatic support.

5.4 Discussion Summary

Social networks provide a wealth of information on respondents; translating that information into practice, however, can be difficult. Using children’s playmate networks in Afghanistan, there were clear structural and compositional effects that had direct impact on programming. Using descriptive and visual information about networks were equally useful for using networks to craft better and stronger interventions.

For the Partnership for Advancing Community Education – Afghanistan (PACE-A), the following recommendations might have helped an already strong intervention:

- Explicitly build playtime into the school day for children to increase the number of ties they have with other children;
- Identify and focus on isolates, either integrating them into the network or crafting strategies to help them succeed independent of others;
- Understand if hierarchy or generalized exchange (or both) are present in a network and use that information to develop a peer education system (for hierarchy) or a “buddy” system (for generalized exchange) to reinforce learning;
- Encourage in-school group work (possibly co-ed) to build expertise, where groups are comprised of a few children with strong connections, as well as their affiliates, to encourage triadic closure and denser connections within the network;
- With a “buddy” system, ensure children are paired with others of like ability to best affect individual-level outcomes in math and language; and
- Use visual information (network maps) to identify basic network-based communication approaches.

Accounting for social networks can help organizations and program managers ensure success when opportunities for monitoring, evaluation, and intervention are rare, as was the case in a number of the villages evaluated in PACE-A. By measuring the social network and crafting program elements to account for network features, program managers shift some of the burden from the organization’s active intervention to a passive intervention by relying on the underlying network to ensure better success. For example, building in playtime increases opportunity for tie formation, directly resulting in more connections in the network and more avenues for influence. Identifying isolates can better craft interventions for marginalized children. Prior, a manager may just be able to say, “These children are lagging; let’s work individually with them.” However, some of those children are likely tied into the network and could be influenced through the network (i.e., instituting a “buddy” system where student pairs work with each other to reinforce learning and knowledge), while others are going to be isolated and will actually need individual support.

One of the really interesting things social network structure provides is an opportunity to understand the types of hierarchy that might be present in a village. This can have important consequences on learning modalities. Within a network showing strong hierarchy among children, a peer leader/education system may be more effective than the buddy system discussed above. If children respond to the hierarchy, then it can be used as an effective way to reinforce learning. Moreover, the strong homophily effects – especially for performance – are indicative that children working together should be of a similar ability, which can help them both succeed. Often, people believe stronger performing students should help weaker performing students, but these homophily effects indicate a different story. Reinforcing learning with someone of a like ability is more indicative of individual success. Finally, in any program, communication is important, whether it is to transmit information on program changes or for recruitment. Understanding the network – especially visually – can help a program manager immediately grasp what strategies may and
may not work in a particular village.

While networks can be important in improving programs, how does one go about getting the information? A primary avenue would be at the needs assessment phase of the project. When an organization or program manager goes to the village for the initial needs assessment, they could add in network elicitation (Valente and Pumpuang, 2007). For contexts like PACE-A, where boundaries are clear (i.e., the village), then a complete network approach probably works best. This involves, for example, talking to all children within the target range of the intervention and asking the network elicitation question (cf. Marsden, 1990; Wasserman and Faust, 1994). In this case, two questions were asked: who in this village is your friend; and, who in this village do you play with? One could cap the number of nominations (e.g., eight nominations) or allow the children to freely name other children (cf. Lubbers et al., 2006).

A second approach may be a personal network approach. This may be more effective, for example, in an urban context, where boundaries are fluid (e.g., school catchment area or neighborhood boundaries) or there are too many children to possibly interview. Here, a sample of children can be selected and asked to name all of their playmates and/or their friends. They then provide some information on each of these children (note, given the age of children, this might be best kept to a limited set of questions) and most importantly, they indicate whether the named peers are playmates/friends of each other (Marsden, 1990; McCarty, 2002; McCarty et al., 2007). This provides valid social networks for the respondent, but it only considers the immediate ties around the respondent; there are novel ways of combining personal networks for respondents answering on children in the same catchment area to better approximate a complete network (Oster et al., 2013), though these approaches need to be balanced against privacy concerns of the children named, but potentially not surveyed.

With these network data – and any other survey information collected from the children, like test scores – the analyses undertaken here can be replicated. Even if strategies are simpler than these presented here, basic network information like the level of connectedness in the network, the spread of ties across the network, isolates, and a visual depiction
of the network can be immensely helpful for an organization or program manager looking to improve the impact and success of their program.
Chapter 6

Conclusion

In chapter 1, three research questions and one policy question were proposed. These questions were:

- Research Question 1: What are the features of playmate networks’ tie formation amongst children in rural Afghan villages? In other words, what are the network structural effects that govern relationships between children?

- Research Question 2: What social cognitive effects (human-to-human interactions) affect children’s behavior with respect to school performance, controlling for network structural effects? Moreover, are there spatial effects that mediate human-to-human interactions with respect to educational outcomes?

- Research Question 3: How do environmental factors, network structure, and social cognition interact to affect children’s learning in rural Afghanistan?

- Policy Question: Given results on environmental, structural, and cognitive effects on student achievement, in what ways can social networks be used to strengthen education interventions in the developing world?

These questions served as the basis of investigation throughout this study. Chapter 1 provided the context for the study, the recent history of Afghanistan, and discussed why strengthening interventions was important within development. While evaluation tools,
like randomized control trials, in development have proliferated recently and provided solid evidence of program effectiveness, fewer resources have been dedicated to figuring out how to strengthen existing interventions when monitoring and evaluation proves difficult or impossible. The chapter concluded by proposing the use of social network information to strengthen and improve interventions at low cost and with minimal additional oversight, thereby increasing the sustainability of the intervention or program in resource-constrained settings.

In chapter 2, a hybrid model of social cognitive theory (Bandura, 1986) and social impact theory (Latané, 1981) related environmental, structural, and cognitive factors to behavioral outcomes. These factors incorporated personal and environmental characteristics, the structure of ties a person maintained with others, and characteristics of a person’s relationships with others as variables influencing one’s behavioral outcomes. This model led to an investigation of how personal and environmental variables affected individual outcomes, what was known about how network structure was associated with behavior, the ways in which others’ behaviors and actions influenced personal decisions, and finally, how social network information has been used to modify existing programs to improve an intervention. The chapter concluded by introducing the data used – village, household, individual, and network information from children in 31 rural Afghan villages as it pertained to academic achievement outcomes within the PACE-A community-based schools program.

A two-step procedure, discussed in chapter 3, was used to estimate how environmental, structural, and cognitive aspects of children and their playmates affected individual learning outcomes. The first step involved estimating exponential random graph models (ERGMs) – a class of network statistical models that utilize network structure and compositional information to predict tie formation – for each of the 31 villages surveyed. The Markov chain Monte Carlo process for estimation, as well as the goodness-of-fit of the models, were assessed after estimation. The \( t \)-statistics from the ERGMs were then used as a village-level vector of coefficients to model structure and cognition at the individual level using multi-level models (MLMs). These MLMs – children nested within households
nested within villages – then related the conceptual model discussed in chapter 2 to children’s learning outcomes by modeling individual and household choices as environmental variables and network structure and composition – as estimated in the ERGMs and translated to the MLMs – as structural and cognitive variables. These results were found in chapter 4.

Finally, chapter 5 laid out the impact chapter 4’s results could have for organizations and program managers looking to utilize network information to improve programming. Recommendations included utilizing networks to better understand the population at the heart of the intervention, what the structure of the network was like, and how to efficiently target individuals within the network. These aspects could help an organization or program manager improve on the effectiveness and sustainability of their program at minimal cost and with minimal oversight.

In this current chapter, I review each research/policy question, discuss evidence for or against the hypotheses, and relate the results back to the literature discussed in chapter 2. I conclude with a summary of findings and recommendations.

### 6.1 Network Structure and Relationships

The first research question touched on the basis of network structure for children’s social network ties. Between the playmate and friendship networks, playmate ties were denser. It was hypothesized that friendship ties constituted a more formal arrangement of social structure than playmate ties. Therefore, it was expected that playmate ties would be denser. In addition, the frequency of isolates was greater in friendship than playmate networks. This finding underscores the need to consider the type of tie best linked to one’s outcome of interest. Whilst demographic comparisons assessed both friendship and playmate ties, MLM results were based solely on ERGMs estimating playmate relations; results could differ if the analysis was repeated with friendship ties.

Descriptively, the centralization of the networks of children was quite low. Akin to a standard deviation, degree centralization is a measure of dispersion of ties within the network. There networks were decentralized, indicating that very few children were “stars.”

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\(^1\)In social networks, a “star” is a person with many ties; it is so named because visually, the person is
which differed from the findings in Daniel et al. (2013). Looking at the social networks of preschool children in Portugal, Daniel et al. (2013) found that in each of the 19 classrooms analyzed, there were at least a few students with outsized popularity. Daniel et al. also found that triadic closure was high (different in these networks) as was reciprocity (the same in these networks). An alternate theory could be that these networks in Afghanistan are developing as networks did in Schaefer et al. (2010), whereby simple structure, like ties and reciprocity, were precursors to more advanced configurations, like triadic closure and cycles. These are indications that cultural and social factors may impact tie structure, meaning configurations of ties can differ dramatically from context-to-context.

In many networks, isolates may differ culturally, socially, and demographically from non-isolates in the network; this makes them interesting in terms of how to intervene within the context of a program. Structurally, they are difficult to reach. In these networks, isolated children were both demographically different from others and difficult to reach structurally. Isolated children, in a network sense, were younger, performed worse academically, attended school less often, and had lower absolute levels of education than non-isolates. Reaching isolates is often difficult (Angelucci et al., 2010; Almquist, 2011). To do so requires specific strategies and outreach to either focus individually on an isolate, or better, induce them into the network via ties with others.

Moving beyond descriptive statistics about networks to the ERGM results, these networks tended to show fairly simple structure. There were very few triadic effects (twopaths, triadic closure, cyclic triples) within the network, though conditioning on lower-order network structures, there was more triadic closure (GWESP) than one would expect by chance. It could be that these children have yet to develop more complex network tie formation. Or, the lack of more complex network structure may be due to some aspect of life in rural Afghanistan. Many of the ties between children were reciprocated; this tight linkage from person-to-person may impact children’s ability to broaden out into triads or link triads together to form larger, more well-connected components. Given Afghanistan’s recent history, relying on strong connections to well-trusted individuals may

at the center of diagram with many arms extending out in the shape of a star.
be a strategy that has been adopted by young children and their early life connections.

Once aggregated to the MLM estimations, overall network structure showed a minor association with children’s academic achievement. First, all network effects were at the village level, which described a relatively small portion of variance in the networks (see table 4.11). Second, only the edges and GWESP terms were significant for math and language achievement structural specifications. Both of these terms were negative, indicating fewer ties (edges) or greater triadic closure (GWESP) were associated with less academic achievement. Combined with a density result that indicated greater density was associated with less academic achievement, there may be a “middle ground” in terms of overall ties that can benefit a child’s performance.

Latané indicated that as the message being transmitted is diffused amongst more people (divisional effect, from figure 2.1), the impact of the message lessens as well. This is akin to the density within the village increasing – with more children connected to one another, the impact of the message on any particular child decreases; however, having some minimum level of connection within the network (represented by an increasing number of edges) is important for a base level of learning. A possible mechanism is that with greater density, there is more opportunity for the message to get garbled when children consult other children for clarification. The strength of the message may be increased when density is lower, as children may have to consult the source (i.e., the teacher) for reinforcement on the message.

In summary, there were noteworthy structural features of these children’s networks. There were people completely outside the network that deserved special attention; however, within the network, there were tendencies seen in other networks, such as a cascade of network structure (cf. Schaefer et al., 2010). That is, while network structure was still simple, important pre-cursors of advanced network structure, such as a significant amount of triadic closure, were observed. With time or active intervention, these advanced network structures could further develop within these children’s networks, providing more opportunities for networks to impact learning outcomes.

There was also evidence supporting the part of the conceptual model that focused
specifically on network structure. Both the force effect and the divisional effect (i.e., the strength with which a message is delivered and the size of the audience that receives the message, respectively) were supported by evidence in the modeled networks. As the number of connections in the network increased, academic performance also increased. This could be interpreted as more connections open up more pathways for message transmittal; however, as the abundance of ties proliferates and density increases, the divisional effect may take some of the force effect away. As density increased, there was a tendency for children’s performance to suffer, indicating that the message from the source was replaced, potentially by seeking reinforcement from other peers, for example. This indicates that there may be a certain number of ties needed for performance increase, though an over-abundance of connections may negatively impact performance. This is where advanced structure, such as cyclic triples, may help. Being in a small group where peer knowledges can be shared and questioned by others may provide a check on any false information, while reinforcing true information.

For policy, utilizing structure can have implications at the network and individual levels. First, at the level of the network, a program manager could work to advance children’s ties from some of the more simple structures seen to more advanced configurations, like transitive triplets or cycles. This helps facilitate a more robust network and may help sustain the program or intervention in the case of a teacher absence or inclement weather that stops input deliveries. However, at the individual level, the role of networks is less clear. There were few aggregate network structural effects on individual achievement, but this may be due to the lack of fully developed network structure.

6.2 Cognitive Effects of Relationships

Cognitive effects, operationalized as the network influence of characteristics like gender or peer academic performance, on individuals were quite strong in these networks. A review of the network visualizations in appendix A indicates one or two large components in most networks and the attributes of these networks also indicate gender and age homophily. Children tended to befriend others like themselves in terms of gender especially; in five of
the 31 networks, there was complete gender segregation.

The cognitive ERGM specification found very strong homophily effects for gender. This was not surprising, as children in other contexts have displayed strong gender homophily in network ties as well (Lubbers, 2003; Goodreau et al., 2009; Lubbers et al., 2010; de la Haye et al., 2010). Unlike, for example, de la Haye et al. (2010), these networks were not broken apart by gender for analysis. Thus, the small amount of cross-gender linkage was retained, though it meant in the five networks with complete gender segregation, no ERGM could be estimated. Keeping the full integrity of the networks was done to maximize the number of nodes in any given network; otherwise, some networks would have been quite small (\( n < 15 \)).

Also in the ERGM estimations, there were fairly strong performance homophily effects for math, with lesser effects seen for language performance. These effects – indicating that children tended to play with others that performed at a similar level to them in math and language – were important to recognize, as it shows that children gravitate towards others who are of a similar ability.

In the GIS model, distance effects were tested. These effects looked at the pairwise distance (in kilometers) from every child in the village to every other child,\(^2\) such that for ties between children, the distance between them was another covariate in the model. Three types of geographic ties representing reciprocated ties, sending (outdegree) ties, and receiving (indegree) ties were tested within the ERGM models. In essence, this covariate matrix of ties tested whether or not the probability of a tie between two children was significantly affected by the distance between the children. For children tied to other children through mutual, sending, or receiving ties, distance was an important association in tie structure between children. In each case, the parameters were negative, which indicated that as distance between two children increased, the likelihood of a tie between them decreased. In other words, children, unsurprisingly, were more likely to play with children who were proximally close.

Practically, this helps a program manager understand more about how they might

\(^2\)Children from the same household, therefore, have a distance of 0 kilometers.
manipulate tie structure within a network. By coming to school, children are introduced to other children who may not be proximally close in the village; these children are therefore unlikely to be tied with one another. A simple way to expand the density of connections within the network would be to create opportunities for children that are proximally distant to interact.

While the ERGM results were important in understanding how certain characteristics were related to how children associated with each other, the primary concern was how networks impacted academic performance. For this, MLMs were used. For math, both gender homophily and math performance homophily had important effects on children’s achievement. First, gender assortment (high homophily) tended to be negatively associated with children’s math performance. That is, some level of cross-gender ties may have been helpful in improving learning outcomes. How this mechanism works is unknown. It could be that boys and girls approach academics differently and therefore can mutually benefit from each other’s learning. However, other hypotheses are plausible.

Performance homophily (for math) was also important for children’s math achievement. In this case, having friends that were of a similar ability was associated with improved math achievement. This lends support for tracking within schools so children have the best chance of success. Using a network-based approach could facilitate tracking: knowing the ties children maintain, children could be purposefully placed in groups where performance could be reinforced, while providing the chance to develop stronger ties with others. Since most PACE-A schools had one classroom with children of various ages and abilities together, groups based on ability may produce efficiencies in learning for children; they can work with peers at a level commiserate with their ability. These might be partially co-ed so that some gender heterophily might influence performance. For language achievement, similar gender and math performance homophily effects were seen; however, language performance homophily was also important in the same ways that math performance was important on academic achievement.

Decreased distance between children with reciprocated ties was also associated with math, but not language, achievement. Interestingly, math homophily affected language
performance, but not vice versa, and decreased distance affected math performance but not language. In terms of math homophily, it could be that there is some transferable skill in terms of mathematics that is beneficial for language performance; however, this deserves further inquiry in subsequent work. Moreover, in terms of distance, it could be that having playmates close by was only marginally beneficially; children tended to do better on the math, rather than the language, assessment, so any benefit from being close to playmates may affect math instead of language performance. Again, further research is needed to better understand this differential.

Ultimately, these cognitive effects have important implications for the implementation of PACE-A. Children’s relationships are important, but the characteristics of those whom they are tied is also important. Using some of this information – such as grouping children based on ability – may help reinforce sustainable learning outcomes. Moreover, distance was an important predictor in math achievement. Relying on multiple findings, if one knows where children live and their academic ability, then groups of children in school could be formed to not only develop stronger tie structure, but geographically-grouping children provides an extra resource – children will have others nearby to turn to for academic help outside of school to improve their learning.

### 6.3 Affecting Outcomes – Environment, Structure, and Cognition

While sections 6.1 and 6.2 discussed how networks affected children’s educational achievement, there were a multitude of effects that impacted how children learned more broadly. The multi-level models used in chapter 4 were a result of understanding that children’s achievement depended on their innate ability, household influences, and village and network norms. These villages were quite insular, given the physical separation between them. So while in many contexts, village or town norms might not affect children’s achievement, in this context, these effects may be important.

In all three models, individual-level effects (i.e., at the child level) were the strongest drivers of academic achievement. This is not unexpected; children are evolving and curi-
ous beings and their ability and inquisitiveness will be paramount in their achievement. While boys outperformed girls, as Burde and Linden (2013) discussed, the gap between boys and girls decreased dramatically from pre-PACE-A levels. Older children also did better than younger, which is unsurprising, given older children’s more advanced cognitive development. Having had more schooling and regularly attending PACE-A were also predictive of academic success generally. Finally, at the child level, there were clear network effects. Children that sent and received more ties to others did better in math and language. This indicated that a level of sociality was associated with academic performance; other studies, such as Haynie (2001), Almquist (2011), and Cappella et al. (2012) also found degree to be an important predictor in behavior outcomes. The cause here, however, is unknown; it could be that these children are more socialized and that affected learning or that greater connections to others is helpful in the learning process (i.e. they have others they can turn to for help or guidance).

However, at both the household- and village-levels, there were important effects associated with child achievement, though they were generally less important than individual-level effects. As discussed earlier, there were both network structural and cognitive effects on students academic performance, and for some of the MLM specifications, village-level modal identity affected achievement; this may have been due to a strong group identity that, like Verdery et al. (2011) with family and kin ties, indicated strong personal connections in the nearby geographic domain. At the household-level, the years of education that the head of household had was associated with both math and language achievement by children. This was unsurprising, though the mechanism for this relationship is also unknown. Greater head of household education may be indicative of stronger norms around education or it could indicate greater resources for the child to tap into, or both. For language achievement, norms around corporal punishment for children were also associated with achievement. In households with more positive attitudes towards corporal punishment, achievement suffered. The inclusion of variables around household norms and parental aspirations were inspired by work of Fan and Chen (2001) and Aturupane et al. (2013), though for the most part, findings on parental aspiration and household
norms were not present in these data from Afghanistan.

While the majority of the variation in the MLM was explained at the individual level, including effects for both household and village were important considerations in capturing the nuance of effect on children’s academic success. Simply considering individual-level factors obviates the important role both households and villages may have had on student achievement. Especially in the realm of network effects, both structure and cognition – measured at the village level – added valuable information to understanding and interpreting factors associated with children’s academic achievement.

6.4 How to Use Networks to Strengthen Interventions

While the fact that network effects existed in these children’s social networks was interesting, ultimately, their value lies in how an organization may utilize these findings for programmatic improvement. In Paluck (2011) and Paluck and Shepherd (2012), peer leaders took an important role in spreading a culture of anti-harassment and tolerance. Utilizing peer nominations to identify leaders, authors were able to construct peer groups that would be most effective at spreading and institutionalizing messages within the network. Similarly, Valente and Pumpuang (2007) discussed ten techniques to identify opinion leaders to help institute behavior change. While each of these methods had advantages and disadvantages, utilizing the social network of a population upon which one is intervening is a productive and useful way to ensure that change is adopted and spread by those that are affected by it. In the context of these Afghan networks, one could identify peer leaders through nominations; however, identifying both male and female leaders is important, given the high levels of gender segregation present in these children’s social networks.

There are a number of concrete and effective policy prescriptions one might enact to improve educational programming and ensure programmatic success in lieu of strong monitoring, evaluation, and oversight. First, encouraging time to develop ties is a primary driver to increase the density of the network. Increasing density could happen through increased playtime at school or simply through the introduction of group activities at
school. Children will capitalize on opportunities to interact; a program manager just needs to set the conditions. This could have the effect of developing more complex structure amongst children (e.g., triadic closure), but also, it could be a driver to bring isolates into the network. This would allow a program to better reach those with limited connections and identify an appropriate targeting strategy for improving their performance.

Moreover, the presence of reciprocity effects, but lack of higher-order effects, such as cycles and transitive closure, seem to indicate ways to advance network development and academic achievement. While PACE-A was not specific to accelerated learning, the age catchment for the program (ages six to 11) was broad enough to think that older students just beginning their academic studies may be better off with more individualized and advanced learning opportunities. Using network structure to determine whom these older students are tied to, and their level of performance, a program manager could work with a teacher to create peer groups that would allow students to work at an independent pace with similar peers. The type of connection, when developing more ties, also matters. For older children trying to advance quickly, it may be more effective to try and induce cycles, where everyone is on “equal” footing with each other, so that knowledge transfer can be a group process, instead of a hierarchical one. However, for younger children, having a hierarchy in ties (i.e., an older peer helps direct learning for younger children) may be more beneficial that a cycle.

Regardless of ability level, peer groups to reinforce or advance learning would benefit students. There were strong performance homophily effects, indicating that students of like ability were more likely to be friends with one another, and that greater homophily in performance in the networks was associated with better overall student achievement. In other contexts, grouping students based on performance is known as tracking. In this context, there is evidence that tracking could benefit student’s achievement. Given classes in the PACE-A program were relatively small, tracking may best be done by building a “buddy system” where students team up in groups of two or three to support each other’s learning. This does not need to be done directly; it could be more natural by grouping chairs or mats together and allowing children to develop an affinity for utilizing their
playmates for academic help.

While gender homophily was a strong component of these networks, it actually had a negative effect on overall student achievement. That is, the multi-level models indicated that more cross-gender ties could be beneficial in improving student achievement. However, care should be used when creating policy guidance from this result. There may be cultural aspects to how and why gender affects both network structure and achievement that were not fully captured in the models. Moreover, non-specific to Afghanistan, children’s networks often show high levels of gender homophily (Goodreau et al., 2009; de la Haye et al., 2010; Lubbers et al., 2010), so it may be that with time, greater levels of cross-gender ties may develop on their own.

Development organizations – especially in difficult operational environments like Afghanistan – constantly have to confront the trade-off between programming desires and operational constraints. Often, actions like monitoring and evaluation can be sacrificed in an effort to make sure the organization meets minimum operational requirements. However, the organization loses an opportunity to learn about and improve the program in this scenario. This study proposed using social networks, which are naturally occurring, to help improve an organization’s programming. It was done in the context of a rural schooling program in central Afghanistan. Results indicated that with some fairly simple data collection, a program manager could bring to the program advanced knowledge on how social network information could improve programming. This would help build redundancy in academic programming (e.g., if students are learning from one another as well as the teacher, a short-term school closure may be less severe on children’s learning) and ways for a program manager to identify those struggling (i.e., identifying isolates can help a program manager determine if individualized help is needed or if incorporating them into the network would suffice), amongst others. In short, it builds a cheap, effective, and ever-present layer of sustainability into an organization’s programming. Using social networks does not replace the need for monitoring and evaluation to learn and capitalize on success within the program, rather, it maintains and extends program reach when operational constraints are reached by utilizing local, specific information to the locale.
And most importantly, networks can help students achieve better long-term outcomes.
Appendix A

Network Visualizations

Each of the 31 village playmate and friendship networks are visualized below. The graphs are arranged using the Fruchterman-Reingold force-directed algorithm on the playmate networks (Fruchterman and Reingold, 1991). This algorithm set the placement of each child in the graphs for both the playmate and friendship networks to facilitate comparison of children across networks. The playmate network was chosen to set node placement since for all villages, it is the denser network. Since the force-directed algorithm maximizes placement based on total edges, it makes sense to use the denser network to set the initial node placement.

Each network displays the child’s gender by shape and their age as color. Circles represent girls and triangles represent boys. Age is represented on a continuous scale using a color gradient from blue (youngest, age 6) to red (oldest, age 11). Arrowheads represent the direction of the nomination, with the node adjacent to the arrowhead being the nominee and the node adjacent to the tail being the nominator. The visualizations were produced in R 3.0.0 (R Core Team, 2013), using a custom-made function relying on the ggplot2 0.9.3.1 (Wickham and Chang, 2012) package.
Figure A.1. Playmate/Friendship Network Visualizations – Village 1
Figure A.2. Playmate/Friendship Network Visualizations – Village 2
Figure A.3. Playmate/Friendship Network Visualizations – Village 3
Figure A.4. Playmate/Friendship Network Visualizations – Village 4
Figure A.5. Playmate/Friendship Network Visualizations – Village 5
Figure A.6. Playmate/Friendship Network Visualizations – Village 6
Figure A.7. Playmate/Friendship Network Visualizations – Village 7
Figure A.8. Playmate/Friendship Network Visualizations – Village 8
Figure A.9. Playmate/Friendship Network Visualizations – Village 9
Figure A.10. Playmate/Friendship Network Visualizations – Village 10
Figure A.11. Playmate/Friendship Network Visualizations – Village 11
Figure A.12. Playmate/Friendship Network Visualizations – Village 12
Figure A.13. Playmate/Friendship Network Visualizations – Village 13
Figure A.14. Playmate/Friendship Network Visualizations – Village 14
Figure A.15. Playmate/Friendship Network Visualizations – Village 15
Figure A.16. Playmate/Friendship Network Visualizations – Village 16
Figure A.17. Playmate/Friendship Network Visualizations – Village 17
Figure A.18. Playmate/Friendship Network Visualizations – Village 18
Figure A.19. Playmate/Friendship Network Visualizations – Village 19
Figure A.20. Playmate/Friendship Network Visualizations – Village 20
Figure A.22. Playmate/Friendship Network Visualizations – Village 22
Figure A.23. Playmate/Friendship Network Visualizations – Village 23
Figure A.24. Playmate/Friendship Network Visualizations – Village 24
Figure A.25. Playmate/Friendship Network Visualizations – Village 25
Figure A.26. Playmate/Friendship Network Visualizations – Village 26
Figure A.27. Playmate/Friendship Network Visualizations – Village 27
Figure A.28. Playmate/Friendship Network Visualizations – Village 28
Figure A.29. Playmate/Friendship Network Visualizations – Village 29
Figure A.30. Playmate/Friendship Network Visualizations – Village 30
Figure A.31. Playmate/Friendship Network Visualizations – Village 31
Appendix B

Survey Instruments

There were five survey instruments used in data collection; they were a household survey, a survey of the head-of-household, a mathematics/Dari exam of children, a friendship/playmate nomination elicitation of children, and a school monitoring form. These instruments were described in detail in Chapter 2.
The following is the survey that should be administered at the household level. This survey should be administered to the most responsible person in the household willing to respond to the survey. Answers should be recorded on the Household and Child Answer Form.

I am [say your name]. I work with researchers from Columbia University. I am here to talk with you about your household and about education in your village.

We are studying community-based schools in Ghor province. We are working with an NGO called CRS who has a program to place schools in villages through Ghor province and we are conducting a study to understand the effects of these schools on children's learning. We would like to survey your household now and again next spring. Please understand that your responses to this survey will have no effect on CRS’s decision about whether or not to help your village establish a school.

To understand more about children’s learning, I’d like to talk with you about your household and your school-age children (6-11 year-olds). In addition, after you and I talk, I would like to interview the children individually (only the 6-11 year-olds) and give them a short test (math and Dari), if that is ok with you. I have an interview form that I will show you. It will take about 20 minutes per child.

Your participation may help us understand the process of delivering better education services in Ghor province. You can end this interview at any time.

The answers to the following questions should be written on the Household Registration Form.

HQ 1. Are you willing to let me talk to you and to let me talk to your children? (Mark only one answer.)
   A. Someone was available and willing to be interviewed.
   B. The household was at home, but refused to be interviewed.
   C. No one was present at the household at the time of interview.

HQ 2. What is your name? (Write name.)

HQ 3. What is the name of the head of the household? (Write name.)

HQ 4. How long have you lived in this village? (Write number of years.)

HQ 5. How do you describe your household? (Read all answers in order before the person responds and mark only one answer. Be sure to read all of the choices before the person responds.)
   A. Pashtun
   B. Farsi Speaking
   C. Hazara
   D. Tajik
   E. Dari Speaking
   F. Afghan
G. Aimaq
H. Other

Read: I would now like to ask you a few questions about the person who provides the most financial support (comak-e-mali) for the household.

HQ 6. What does the primary financial supporter for the household do?
   (Mark only one answer.)
   A. Farmer
   B. Shopkeeper
   C. Teacher
   D. Trader
   E. Civil Servant (excluding teacher)
   F. Daily Laborer
   G. Raises livestock (maldari)
   H. Other

HQ 7. How old is this financial supporter?
   (Write number of years.)

HQ 8. For how many years did this financial supporter go to a school or madrasa?
   (Write number of years.)

Read: Now, I would like to ask you a few questions about your household in general.

HQ 9. How many people live in your household?
   (Write total number of people.)

HQ 10. How often does your household eat meat?
   (Mark only one answer.)
   A. Every day.
   B. Once a week.
   C. Once a month.
   D. Less than once a month.

HQ 11. How many jeribs of irrigated land does your household have?
   (Write number of jeribs.)

HQ 12. How many sheep and goats does your household have?
   (Write total number of sheep and goats.)

HQ 13. How many children live in your household who are from six to eleven years old?
   (Write total number of children.)

Read: Now, I would like to ask you about children and education.

HQ 14. Compared to the future a boy would have without an education, with an education a boy will:
   (Mark the letters of the THREE outcomes the parent considers most important.)
HQ 15. Compared to the future a girl would have without an education, **with an education** a girl will:

(Mark the letters of the THREE outcomes the parent considers most important.)

- A. Provide a better future for her family
- B. Have a better job
- C. Be able to marry better
- D. Be better socialized (have better *tarbia*)
- E. Be a better Muslim
- F. Be a better citizen of Afghanistan
- G. Contribute more to our household

HQ 16. For a boy that goes to school, what must he be able to learn?

(Mark the letter of all answers mentioned.)

- A. He must be able to read the Koran.
- B. He must be able to read and understand the Koran.
- C. He must be able to read and write in Dari.
- D. He must be able to do math problems.
- E. He must be able to help his own children in the future learn the Koran, Dari, and math.
- F. He must be able to study for higher education outside the village.

HQ 17. For a girl that goes to school, what must she be able to learn?

(Mark the letter of all answers mentioned.)

- A. She must be able to read the Koran.
- B. She must be able to read and understand the Koran.
- C. She must be able to read and write in Dari.
- D. She must be able to do math problems.
- E. She must be able to help her own children in the future learn the Koran, Dari, and math.
- F. She must be able to study for higher education outside the village.

HQ 18. What is the best age for a boy to stop going to school?

(Write in age.)

HQ 19. What is the best age for a girl to stop going to school?

(Write in age.)

Read: Next, I have some questions about parents punishing their child.
Columbia University -- Community Schools Study
QUESTIONNAIRE ONE: Household Questionnaire

HQ 20. If a child has not completed a chore that was asked of him/her, what should a parent do?  
HQ 21. If a child beats his/her brother or sister, what should a parent do?  
HQ 22. If a child has not finished his/her schoolwork, what should a parent do?  

ANSWERS FOR HQ20 – HQ22  
A. A parent should explain to the child what they did wrong.  
B. A parent should take away a child’s privilege, like playing with friends or flying a kite.  
C. A parent should yell at the child.  
D. A parent should beat the child.  
E. The child does not need to be punished.

Read: Now I have some question about teachers punishing students in school.  
HQ 23. If a student is sleeping in class, a teacher should do what?  
HQ 24. If a student is disruptive in class, a teacher should do what?  
HQ 25. If a student hits another student, a teacher should do what?  
HQ 26. If a student has not finished his/her schoolwork, a teacher should do what?  
HQ 27. If a student is late to the lesson, a teacher should do what?  

ANSWERS FOR HQ23 – HQ27  
A. A teacher should make a child stand in the corner of class.  
B. A teacher should make a child do extra homework.  
C. A teacher should beat the child.  
D. A teacher should meet with the child’s parent.  
E. A teacher should tell the student to leave class.  
F. The child does not need to be punished.  
G. A teacher should talk with the student.

Read: For the final couple of questions, I want to know your opinion.  
HQ 28. The central government plays an important role in my children’s education.  
HQ 29. The provincial government of Ghor plays an important role in my children’s education.  
HQ 30. International NGOs play an important role in my children’s education.  
HQ 31. Members of my village play an important role in my children’s education.  
HQ 32. I have trust in the central government of Afghanistan.
HQ 33. I have trust in the provincial government of Ghor.
HQ 34. I have trust in international NGOs that work in Ghor province.
HQ 35. I have trust in my neighbors in my village.

ANSWERS FOR HQ28 – HQ35
A. Yes
B. No
C. No opinion
B.2 Head-of-Household Survey

The answers to all the remaining questions should also be recorded on the Household and Child Answer Form. Add additional forms for the household if necessary (if there are more children in the household than are accounted for on the interview form), but make sure to fill out the information at the top of the form properly.

Read: I would now like to ask you some questions about the children who live in your household.

Please give me the name of each child who is from six to eleven years old who lives in this household.

(Write name of each child on the Household and Child Answer Form.)

Now I would like to ask you some questions about each of these children.

(Ask the following questions about each child and record the answers on the Household and Child Answer Form.)

CQ 1. How is this child related to the head of the household?
   (Mark only one answer.)
   A. Head of household’s son.
   B. Head of household’s daughter.
   C. Head of household’s nephew
   D. Head of household’s niece
   E. Head of household’s brother
   F. Head of household’s sister
   G. Other

CQ 2. Is this child a boy or a girl?
   (Mark only one answer.)
   A. Boy
   B. Girl

CQ 3. How old is this child?
   (Write number of years.)

CQ 4. For how many years has this child gone to a school, madrasa, or mosque?
   (Write number of years.)

CQ 5. Does your child support the household by doing any of the following things?
   (Wait for a response after each question. Write down the letter that corresponds to each answer the parent mentions.)
   A. Sell produce in the market
   B. Gather fuel (for example, firewood, dung, etc.)
   C. Herd animals
   D. Work in construction
   E. Weave carpets
   F. Work in a shop (shopkeeper)
G. Care for children
H. Pick fruit
I. Fetch water
J. Wash clothes
K. Cook food or make bread
L. Other
M. My child does not support the household livelihood

If the answer to question number 5 is “M. My child does not support the household livelihood”, then place an “X” in the box for question 6 and skip to question number 7.

If the answer to question number 5 is any other answer other than “M” then continue on to question 6.

CQ 6. Does your child get paid for any of these things? (Mark only one answer.)
A. Yes
B. No

CQ 7. Did your child live in this village in the spring of this year? (Mark only one answer.)
A. Yes
B. No

If the answer to question number 7 is “A. Yes”, then place an “X” in the box for question 8 and skip to question number 9.

If the answer to question number 7 is “B. No”, then continue on to question number 8.

CQ 8. When did your child arrive in the village? (Write month and year, i.e. MM/YY – 09/07).

CQ 9. Does your child attend studies now? (Mark only one answer.)
A. Yes
B. No

If the answer to question number 9 is “B. No”, then place an “X” in the boxes for questions 10, 11, 12, and 13 and skip to question number 14.

If the answer to question number 9 is “A. Yes”, then continue on to questions number 10, 11, 12, and 13.

CQ 10. What kind of school does the child attend? (Write the letter of each option that applies)
A. Government School
B. Mosque School
C. Madrasa
D. School run by an international NGO
E. Other type of school
CQ 11. Where is the place that the child studies?
   (Mark only one answer.)
   A. Inside village.
   B. Other village – child stays at home each night.
   C. Other village – child does not stay at home each night.

READ: Now I would like to ask you some questions about your child’s recent attendance at school.

CQ 12. On the last day of class, did your child attend studies?
   A. Yes
   B. No
   C. Don’t know

CQ 13. In the last week, how many days did your child attend studies?
   (Write number of days. If the parent does not know, mark the answer with “A. Don’t know.”)
   A. Don’t know

CQ 14. Did your child attend studies in the spring of this year?
   A. Yes
   B. No

If the answer to question number 14 is “B. No”, then place an “X” in the box for question 15 and skip to question number 16.

If the answer to question number 14 is “A. Yes”, then continue on to question number 15.

CQ 15. Where was the place that your child studied?
   A. Inside village.
   B. Other village – child stays at home each night.
   C. Other village – child does not stay at home each night.

CQ 16. Is the child here and can I interview this child individually now?
   (Mark only one answer.)
   A. Yes
   B. No

If any of the children are available to interview, take the child aside and administer the “Child Questionnaire for Child” to each available child.
B.3 Child Examination

Columbia University -- Community Schools Study
QUESTIONNAIRE THREE: Child Questionnaire for Child

The following survey should be administered to every child between the ages of six and eleven (inclusive) in the household. Please interview each child alone.

Start by reading the following to the child:

I am [say your name]. What is your name? [Give the child time to answer.]

I work with parents and children. Right now, I am trying to learn more about the daily life of children like you. If it is ok with you, I would like to give you a short test in math and Dari and to ask you some questions about your friends.

I am going to read you a set of questions. You should give the answer that fits best. If you don’t understand the question, I will read the question again, exactly as it is written on the page. You can ask me anytime to clarify a question. I will record your answer exactly as you tell it to me. Do you understand?

If the child understands, continue. If the child does not understand, ask what the child does not understand and clarify the issue for the child.

Continue reading: You can choose not to answer, or you can tell us if a question is hard for you and we will skip that question. If you like, you can end the interview at any time.

CQ 17. May we have your permission to ask these questions and would you be willing to participate? (Mark only one answer.)
   A. Yes
   B. No

If child answers “B. No”, then thank the child and let the child go. Leave the rest of the questions blank, and start to interview the next child.

If child answers “A. Yes”, then continue to question number CQ 18.
DARI TEST

Now I'm going to ask you the questions for the Dari test.

Read each question exactly as it is written.

CQ 18. Are you able to identify the following letters?

A. ج
B.  ش
C. ب

CQ 19. Are you able to identify the given letter in the following words?

A. قلم  ق
B. نان  ن
C. اطلاق  ا

CQ 20. Are you able to read the following words?

A. نجار
B. سگ
C. موش

CQ 21. Are you able to read the following more difficult words?

A. مکتب
B. دوکاندار
C. پشک
MATH TEST

Now I will ask you about your math skills.

CQ 22. Are you able to identify the following numbers?
   A. 3
   B. 5
   C. 9

CQ 23. Are you able to count the following items?
   A. X X
   B. X X
   C. X X

CQ 24. Of the numbers below, are you able to identify the greater and smaller numbers?
   A. 7 8
   B. 4 4
   C. 9 2

CQ 25. Are you able to complete the following addition?
   A. 4 + 2 =
   B. 7 + 1 =
   C. 2 + 3 =

CQ 26. Are you able to complete the following subtraction?
   A. 3 – 1 =
   B. 5 – 2 =
   C. 8 – 5 =

Read: Thank you for taking those tests for me. I appreciate it. I only have a couple more questions for you.

Now use the Friendship Network Questionnaire (QUESTIONNAIRE FOUR) and mark all answers on the Friendship Network Form.
This survey is a continuation of Questionnaire Three and should be administered to every child that answers questionnaire three. Answers should be recorded on the Friendship Network Form.

Start by reading the following:

Thank you for answering my questions so far. I would like to ask you about your friends and siblings and other children you play with here in the village. Think about the different ways you play with your friends or siblings and which of those children are your friends. Maybe they are the same, but maybe they are different.

FNQ1. Which children in the village do you play with?
(List each name on a separate line on the answer form. Then ask the following questions about each child listed.)

FNQ2. What is [child’s name] father’s name?
(Write the child’s father’s name. If the respondent does not know, ask his/her parent.)

FNQ3. Is [child’s name] your brother or sister?
A. Yes
B. No

(Ask FNQ2 for each name on the respondent’s list. When you have finished asking about the last child, continue below.)

Read: Thank you for telling me about whom you play with. Now I want to ask about your friends.

FNQ4. Which children in the village are your friends?
(List each friend named on a separate line on the answer form. Then ask the following questions about each friend listed.)

FNQ5. What is [friend’s name] father’s name?
(Write the friend’s father’s name.)

FNQ6. Is [friend’s name] your brother or sister?
A. Yes
B. No

(Ask FNQ5 of each friend on the respondent’s list. When you have finished asking about the last friend, continue below.)

Thank you very much for talking with me.

Allow the child to leave. If there are children left to interview, begin interviewing the next child. If there are no more children in the household to interview, be sure you have recorded all of the father’s names listed for FNQ2 and FNQ5 then thank the family for letting us ask them questions and go to the next household.

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B.5 School Monitoring

The following survey should be administered to the teacher of the community-based school in treatment villages ONLY. Record the answers on the Teacher Interview Form.

Start by reading the following:

I am [say your name]. I work with researchers from Columbia University. I am here to talk with you about your teaching and education in the village.

We are studying community-based schools in Ghor province. We are trying to find out how many school-age children (ages 6-11 years-old) are interested in attending community-based schools, and what impact school might have on communities and children. CRS is delivering a community-based education program in this area and is helping us with introductions to the communities where they work. Columbia is not delivering services.

To learn about these things, I'd like to talk with you about the students that attend your classes. The questions relate to their attendance and performance in Dari and math. I have an interview form I will show you. It will take about 30 minutes to complete.

Your participation may help us understand the process of delivering better education services in Ghor province. You can end this interview at any time.

The answers to the following questions should be marked on the Teacher Interview Form.

TQ1. Are you willing to let me talk to you? (Mark only one answer.)
   A. The teacher was available and willing to be interviewed.
   B. The teacher was available, but refused to be interviewed.
   C. The teacher was not present in the village at the time of interview.

TQ2. What is your name? (Write name.)

TQ3. How long have you lived in this village? (Write number of years.)

TQ4. Do you keep daily attendance of your students?
   A. Yes
   B. No

TQ5. Is there a School Management Committee?
   A. Yes
   B. No

If the answer to question number 5 is “B. No”, then place an “X” in the box for question 6 and skip to question number 7.

If the answer to question number 5 is “A. Yes” then continue on to question 6

TQ6. How often does the School Management Committee meet?
   A. Once a week
   B. Twice a month
C. Once a month 
D. Once every two months 
E. Not at all 

TQ7. What are the names of all the children in class? 
(List each child named on a separate line on the answer form. Then ask the 
following questions about each child listed.) 

TQ8. On the last day of school, did [student's name] attend school? 
   A. Yes 
   B. No 

TQ9. In the last week, how many days did [student's name] attend? 
   (Write number.) 

TQ10. How well is [student's name] doing in Dari? 
   A. Very good 
   B. Good 
   C. Average 
   D. Bad 
   E. Very bad 

TQ11. How well is [student's name] doing in math? 
   A. Very good 
   B. Good 
   C. Average 
   D. Bad 
   E. Very bad 

(When you finish all questions for a student, go back and ask TQ8-TQ11 for all remaining 
students. Once you have finished asking about every student, thank the teacher for 
his/her time and move on to household surveying.)
Appendix C

Exponential Random Graph Model

MCMC Diagnostics

Since the concept of Markov chain Monte Carlo (MCMC) methods is to obtain a random sample via stochastic methods, diagnostics testing how well the process worked are an important consideration for the ERGM estimation overall. While sections 4.3 and 4.3.1 focused on the results and goodness-of-fit of the ERGMs, respectively, this appendix focuses on the MCMC diagnostics.

The field of MCMC diagnostics is separate from ERGMs; the methods used below are applicable to any MCMC process, not just those used in ERGM estimation. However, aggregating diagnostic output across multiple MCMC estimations is difficult. Below are visual diagnostics of some important MCMC diagnostics. To start, lag autocorrelations are presented in figures C.1 through C.6. Lag autocorrelation measures the amount of correlation between the present value at a given lag to the original starting value. Ideally, one wants to see autocorrelation decrease relatively quickly to ensure that the draws from the MCMC process are indeed random.

For each lag autocorrelation figure, the panels represent the ERGM terms modeled. Each of the villages estimated has a line; the color of the lines transitions from red to blue, where lower number villages (e.g., villages 1, 2, and 3) are reddest and higher number villages (e.g., villages 29, 30, and 31) are bluest. A average fit across all villages is presented by a black line. Figure C.1 represents the structural model specification.
while figures C.2 through C.3 represent the cognitive model specification, and figures C.4 through C.6 represent the GIS model specification.

In figure C.1, one village performed poorly in terms of autocorrelation lag; its autocorrelation stayed quite high with the starting value, even after 50,000 iterations. However, the overall lag autocorrelation on parameter terms seemed to indicate that by 12,000 lags, there was a marked decrease in autocorrelation amongst draws and the starting value.
For the cognitive model specification, for both structural terms (figure C.2) and compositional terms (figure C.3) the autocorrelation again settled at around 12,000 lags. There was again one village that performed poorly, though not as consistently bad as in the structural model. It is interesting to note – especially with the compositional terms in the cognitive specification – that autocorrelation for some villages fell quite rapidly, by about 2,000 lags.
Cognitive ERGM Specification: MCMC Lag Autocorrelation

For the GIS model specification, in figure C.4, most parameters achieved a low level of autocorrelation by 10,000 lags, though the process was extended out for some of the higher order terms, like GWESP and cyclic triples. For each of the homophily terms modeled in the GIS specification (figure C.5), most villages autocorrelation was quite low by 12,000 lags. As with the cognitive specification on compositional terms, there were a number of villages who achieved small autocorrelation values quite quickly, within a
few thousand lags. Finally, for the distance covariate between children (figure C.6) both of the unidirectional measures (the lower two panels – dyad.upper and dyad.lower) quickly achieved low autocorrelation, though the process was lengthened somewhat for the mutual ties specification (dyad.mutual).

Overall, autocorrelation did not seem to be a strong problem in most villages with the MCMC estimation. For villages were autocorrelation remained high, they were often...
the villages that had failed to converge (analyses not presented). Similar to some of the goodness-of-fit statistics, the failure to converge could significantly affect the post-estimation diagnostics.

A second diagnostic used to understand MCMC functioning was the Geweke convergence diagnostic. The Geweke method compares the mean and variance of a MCMC chain at various points from beginning to end. Over the various lags, the Geweke diagnostic
Figure C.6. MCMC Lag Autocorrelation for the Playmate ERGM GIS Estimation

compares \( z \)-statistic to the standard normal distribution; if \( z \)-statistic fall above or below two standard deviations, then there is indication that additional lags are needed to ensure convergence. In essence, it is testing whether the distribution for the statistic – at given points – is stationary, where stationarity is an indication of convergence.

Again, since there were 31 villages estimated, results have been aggregated for visual inspection using box-and-whiskers plots; these can be seen in figures C.7 through C.9.
For each box-and-whisker plot, each of the three model specifications are presented, with horizontal lines representing the boundaries of convergence.

In figure C.7, across all model specifications, the parameter terms are quite settled. They seem to have reached stationarity with only a few outliers for particular parameters in some model specifications. This is an indication that the MCMC estimation was able to reach a space where parameters terms were consistent and not fluctuating between...
Figure C.8. Geweke MCMC Convergence by Estimation Type – Playmate ERGM Compositional Effects

extreme values. Likewise, in both figures C.8 and C.9, for compositional and distance terms, respectively, parameter terms were quite stationary with only a few outliers.

The final MCMC diagnostic were normalized kernel densities of parameter estimates for each model specification. These kernel densities represent the distribution of parameter term counts over the MCMC distribution. However, for comparability across villages, each
Figure C.9. Geweke MCMC Convergence by Estimation Type – Playmate ERGM Distance Effects

parameter was normalized to a mean of zero and standard deviation of one. This allows comparison across villages of the shape and nature of the kernel density distribution on parameter terms. As with the MCMC lag autocorrelations presented in figures C.1 through C.6, each village is represented across the red/blue color spectrum, where lower numbered villages are red and higher numbered villages are blue.

In many ways, the normalized kernel densities are similar to the Geweke convergence
diagnostic, since the Geweke statistic is measuring if the parameter has reach stationarity, which when the distribution is normalized, would indicate a normal-looking curve. For the structural model specification in figure C.10, the GWIIndegree term has two villages with non-normal density distributions. This could indicate that for these villages, there was trouble in identifying a local maxima in the estimation. Overall though, it seems that difficulties were constrained to two villages, similar to the Geweke diagnostic. Moreover,
subsequent analysis (not presented) indicate for the GWIndegree term specifically, the villages with non-normal distributions had failed to converge in the ERGM estimation.

Unlike the structural specification, the cognitive specification of structural parameter terms (figure C.11 maintained fairly normal distributions across all villages. The higher-order structural terms, like GWESP and cyclic triples, do show a bit of non-normality,
but nothing as extreme as in figure C.10. Likewise, in figure C.12, the kernel densities of the compositional terms of the cognitive model specification maintain normality.

With respect to the GIS model specification, figure C.13 indicates that all structural terms but the GWESP maintained normality; there was one village on the GWESP term that had a left-skewed distribution. While the homophily terms in the GIS model (see fig-
Figure C.13. Normalized Sampled Statistic Kernel Densities of Structural Effects – Playmate ERGM GIS Estimation

ure C.14) seemed to maintain normality, the distance term for mutual ties (DYAD.MUTUAL) and for sending ties (DYAD.UPPER) seemed to have trouble maintaining normality within some villages. To some extent, this coincides with issues in the Geweke convergence.

Overall, the diagnostics of the MCMC estimation seem relatively strong. In most instances, the lag autocorrelation settled to a low amount of correlation within 12,000
lags. Given ERGM estimation was over 50,000 iterations, after roughly the 24 percent of the sample was drawn, the autocorrelation was no more than one might expect by chance. In terms of convergence, the Geweke convergence statistics indicated strong stationarity across villages, with only a few outliers. Finally, while there were some departures from normality for kernel density, across model specifications and terms, the villages indicates
strong adherence to normality in terms of parameter distribution for drawn samples.
For both the Geweke convergence statistics and the kernel densities, aberrations from
stationarity are likely due to the villages that estimated, but failed to converge.
References


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RAND

HEADQUARTERS CAMPUS
1776 MAIN STREET, P.O. BOX 2138
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