Parent Social Networks and Children's Mental Health: Evaluating the Promise of School-Based Family Engagement Programs for Reducing Income-Based Disparities in Children's Mental Health

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Abstract

This paper uses quasi-experimental and experimental methods to evaluate the effect of enriching parent social networks via family engagement programs on social class inequality in children's mental health. First, I estimate the causal effect of intergenerational closure - a social network structure wherein the parents of children's friends know each other and engage in mutually reinforcing social control behavior - on children's mental health for a national sample of 1st graders. To address potential confounding and selection bias, I develop a theoretically motivated propensity score model predicting levels of intergenerational closure, operationalized as how many of their child's classmates' parents that they know. Second, I explore whether family engagement programs promote intergenerational closure for parents with children in first grade in sample of 52 schools enrolled in a randomized field experiment of Families and Schools Together, a popular family engagement program. I exploit the randomized design to identify an unbiased causal effect of FAST on levels of intergenerational closure, and I examine potential effect heterogeneity by pre-treatment levels of intergenerational closure (i.e., the number of parents known prior to the intervention).

Although much can be gleaned from these analyses, applying insights from both unearths a richer set of inferences about the potential effects of family engagement programs on social class inequality in children's early mental health. To do this, I test two policy scenarios using Monte Carlo simulations in order to gauge the potential for reducing inequality. The first reflects a broad implementation of family engagement programs in all schools. The second demonstrates a more targeted approach of offering family engagement programs in high poverty schools. I find that intergenerational closure has a small, but statistically significant causal effect on internalizing problem behaviors but not externalizing problem behaviors. I show that FAST successfully builds intergenerational closure in a sample of 52 high poverty, majority Hispanic schools. The program successfully engages and builds intergenerational closure the most for families that are initially socially isolated. The simulations show that implementing FAST in schools would do very little to substantially improve children's mental health and its impact on social class inequality would be negligible, even if the program targeted high poverty schools. Although the impact of FAST on intergenerational closure is larger than average differences between poor and non-poor families in levels of intergenerational closure, the impact is not large enough to benefit children's mental wellbeing in a meaningful way. However, a larger increase in intergenerational closure than is evident in the FAST experiment could have significant benefits for children.

Parent Social Networks and Children's Mental Health: Evaluating the Promise of School-Based Family Engagement Programs for Reducing Income-Based Disparities in Children's Mental Health

In this paper, I investigate social class inequality in the school-based social networks of parents with young children, particularly regarding connections with other parents of their children's classmates. Theoretically, these sorts of connections matter for children's outcomes because they provide social support, information, and other social resources that can enrich the environments within which children develop. In contrast, parents who are disconnected to school-based parent social networks (i.e., do not know any of their child's classmates' parents) may be missing out on important social resources, even if they have rich networks outside of the school environment. The goals of this study are to describe the school-based social networks of parents from different social classes and to test the whether knowing other parents at the school improves children's mental health. I also examine heterogeneity in the effect of school-based parent networks by family social class.

Prior evidence linking parent social resources to children's mental health faces three major hurdles that this study seeks to address. First, I address the endogeneity concerns of prior work by implementing a propensity score weighting model, theoretically eliminating bias due to a rich set of measured confounders. Second, while prior work has relied on purposively selected regional samples of parents and children residing in racially segregated and/or socio-economically deprived neighborhoods, this study draws on nationally representative data of elementary school-aged children and their families. My results are nationally representative, and the variability in social class allows me examine the effect of school-based parent networks separately for poor, working class, and middle class families. Third, prior studies have focused on family or neighborhood measures of social resources (e.g., informal social control, trust, and cohesion). Instead, I focus on school-based parent networks, arguing that these networks involve individuals with shared issues, concerns, and environments that may have a greater impact on children's mental health than others with whom parents have less in common.

Mental Health in Early Childhood

Mental health, or "the state of balance that individuals establish within themselves and between themselves and their social and physical environment" (Sartorius 2002: 101), is a critical aspect of child wellbeing. Mental health problems, like attention deficit disorder, anxiety, and depression, prevent children from normal social engagement and from pursuing relationships and activities necessary for healthy development.[1] Mental health problems are alarmingly common among children: in the US, in any given year, between 14 and 20 percent of children exhibit signs and symptoms of mental, emotional, or behavioral problems (O'Connell et al. 2009). Children from poor families and who live in areas of concentrated disadvantage are more likely to develop mental health problems (Institute of Medicine 2012).

Children's mental well being, while important in its own right, has been linked to a multitude of outcomes across the life course, such as school attachment, delinquency, substance abuse, risky sexual behavior, depression in adulthood, labor market earnings, and employment instability (Farmer 1993; Caspi et al. 1998; Gregg and Machin 2000; Fletcher and Wolfe 2007; National Institute on Drug Abuse 2007; Substance Abuse and Mental Health Services Administration 2007). Early intervention is crucial for preventing

[1] The distinction between non-cognitive skills and mental health is subtle, and researchers often use similar

mental health problems among children and adolescents. This paper investigates the social environment of children's mental health with a particular focus on parents' social connections with other parents at school. The focus on school-based parent connections holds promise because it constitutes a clear and actionable target for policies that seek to address inequality.

School-based Parent Social Networks

Strong social networks generate valuable social resources for parents that have implications for children. The social support, advice, and commonplace reciprocal exchanges that well-connected parents enjoy promote their own mental health and wellbeing (Cohen 2004; Thoits 2011). The mental health and wellbeing of parents, particularly of mothers, can have lasting consequences for children by reducing the risks to adverse mental health associated with social isolation (Downey and Coyne 1990). Additionally, and perhaps more directly related to school-based networks of parents, forming supportive relationships with others who share common struggles, goals, and expectations helps parents manage daily challenges, especially those associated with having small children. School-based parent networks ensure that parents have many things in common: they are all a part of a shared school community, dealing with the same school staff and policies, and share in many of the same age-based child-rearing struggles. Thus, while supportive relationships with other adults outside of the school communities likely matter and provide some support, the relationships with parents facing similar issues may bring more direct aid to bear when children are first entering school.

In a review of recent evidence the impact of social resources (e.g., social control, trust, social cohesion, and social support) on children's mental wellbeing, Almedom (2005) concludes family and neighborhood social resources, in particular parental monitoring and informal social control, are important determinants of child and adolescent development, health and wellbeing. The studies draw on purposively selected regional samples, many of which are racially segregated and socioeconomically disadvantaged (e.g, Stevenson 1998; Caughy et al. 2003), but some of which sampled from advantaged and disadvantaged populations in order to examine variation in the effects of social resources on children's mental health by socioeconomic factors (e.g. Beyers et al. 2003; Drukker et al. 2003). Neighborhoods with higher socio-economic deprivation and residential instability generally have lower levels of informal social control, social cohesion, and trust (Aneshensel & Sucoff 1996; Kawachi, Kennedy, & Wilkinson, 1999; Drukker et al. 2003). It is difficult for families to establish dense, stable networks of people to rely on if they live in residential areas where many families move in and out on a regular basis or are constantly on the move (Kawachi & Kennedy 1997). A lack of stable ties with others makes establishing a network of parents who can aid in monitoring children's behavior more difficult, thus increasing the risk of children's mental health problems in low SES areas (Drukker et al. 2003).

Following prior work, this study investigates social class inequality in both school-based parent social networks and child outcomes. The emphasis on social class inequality draws from research on patterns of inequality in social capital, a resource embedded within social networks. Access to social capital varies in important ways by social class and race/ethnicity, and scholars have demonstrated that inequality in social capital contributes to—and even reproduces—social inequality (for a review and discussion, see Lin 2000). Few large, quantitative studies have explored social class differentials in social capital, particularly school-based social capital (Dika and Singh 2002). Freeman and Condron (2011) are an exception. The authors show that social capital varies in important ways by social class, demonstrating that middle/upper class parents more often participate in school activities, more frequently interact with other parents, and know more of their children's classmates' parents than working class or poor parents, net of the impact of racial/ethnic differences and family structure.

In addition to varied levels of social capital, social capital may have differential effects. This means that school-based parent networks may not benefit all families and children equally. More advantaged families may have more social connections to the people that matter for securing health benefits, but they also have more economic and cultural resources. So, while their levels of social capital may be higher, they may not actually draw upon those networks in the same way as less advantaged families. Thus, the effect of social capital may actually be weaker for middle class families than poor or working class families. Or, it could be that the networks of poor or working class families constitute similarly disadvantaged families, and those connections may not generate the types of social resources that matter for children's mental health. In fact, some evidence suggests that there are costs to network involvement for low-income families in part because networks of people in poverty are constitutive of individuals who need more support but have fewer resources to offer (Belle 1983; Kawachi and Berkman 2001). Either way, the effect of social connections may vary across social class.

Family Engagement Programs and Building School-Based Parent Social Networks

One source of social class differences in social capital is varied levels of parents' involvement in extracurricular activities and school events (Horvat et al. 2003; Covay and Carbonaro 2010). In addition to more connections, such activities create stronger bonds between children and their families (Offer and Schneider 2007). Middle/upper class parents of school-aged children more often attend school activities and more frequently interact with other parents, net of the influences of racial/ethnic background and family structure (Freeman and Condron 2011). There are also significant barriers to parental involvement in schools for minorities and immigrant families with young children (Carreón et al. 2005; Turney and Kao 2009). Minority and immigrant parents perceive more barriers to involvement (e.g., problems with safety or language, feeling welcome at school, transportation to events), and are less likely to participate in activities at their children's school net of other demographic and socioeconomic variables (Nord and Griffin 1999; Turney and Kao 2009).

Schools are important contributors to structuring opportunities for families and schools to build resourceful connections. One way to address to the problem of differential school-based social capital is to promote family engagement programs within the schools of socially marginalized communities, enhancing opportunities for parents to build supportive relationships with other parents at the school. School-based family engagement programs are built on the premise that the connections made among families and between families and schools are key for educational success. These programs support a broad range of activities designed to enhance children's cognitive and socio-emotional growth, including parent-focused education and skills training, between family bonding activities, parent-child bonding activities, and child-centered experiential learning activities. Thus, differential participation by parents as well as schools that offer programs may generate educational inequality not only from direct effects of differences in the activities themselves, but also because of the social networks they facilitate for parents. Attendance at such programs shapes opportunities for parents to meet, interact regularly, and discuss school-related issues with other parents. Given that children's activities are a central pathway for parental connections, and that more advantaged families have greater opportunity to participate, access to programs for children could be an important policy lever through which to address inequality in parent social resources.

The Current Study

Figure 1-1 is a conceptual model of the processes under investigation in this paper. To empirically evaluate the relations represented in the conceptual model, I integrate multiple data sources, drawing on the compatibility of observational and experimental research designs. In this study, I examine the role of intergenerational closure – a social network structure wherein the parents of children's friends know each other and engage in mutually reinforcing social control behavior – in understanding social class inequality in young children's mental health. In addition, I explore the potential for school-based family engagement programs to boost parent social capital and reduce social class gaps in children's outcomes. By instituting a set of organizational affiliations that bind families in stable, predictable ways, schools play an important part in structuring opportunities for families to build resourceful connections. Investing in school-based family engagement programs could be a powerful way to intervene on parent social networks and social class gaps in child development.

I analyze observational data from the Early Childhood Longitudinal Study - Kindergarten Cohort (ECLS-K), a nationally representative panel study of 21,260 children attending kindergarten during the 1998-1999 school year in 1,000 schools. I supplement analyses of ECLS-K with experimental data the Children, Families, and Schools (CFS) project, a randomized field study of approximately 3,100 families with first graders in 52 elementary schools, half of which were randomly assigned to participate in a family engagement program called Families and Schools Together (FAST). My analysis proceeds in three stages. First, I estimate a multi-level model of the causal effect of intergenerational closure on children's mental health, operationalized as internalizing and externalizing behaviors, in the ECLS-K study (Box A in Figure 1). To address potential confounding and selection bias, I develop a theoretically motivated propensity score model predicting levels of intergenerational closure, operationalized as how many of their child's classmates' parents that they know. Second, I explore whether family engagement programs promote intergenerational closure for parents with children in first grade using data from the CFS study (Box B in Figure 1). I exploit the randomized design of the CFS project to identify an unbiased causal effect of FAST on levels of intergenerational closure, and I examine potential effect heterogeneity by pre-treatment levels of intergenerational closure (i.e., the number of parents known prior to the intervention). Third, I combine statistical parameters estimated from the ECLS-K and CFS data to simulate alternative, sociologically plausible and empirically defensible counterfactual scenarios involving the full set of relations represented in Figure 1. Although much can be gleaned from these analyses, applying insights from both unearths a richer set of inferences about the potential effects of family engagement programs on social class inequality in children's early mental health. To do this, I test two policy scenarios using Monte Carlo simulations in order to gauge the potential for reducing inequality. The first reflects a broad implementation of family engagement programs in all schools. The second demonstrates a more targeted approach of offering family engagement programs in high poverty schools.

Research Questions

1.1) Does intergenerational closure influence young children's mental wellbeing?

1.2) For whom is intergenerational closure particularly important?

1.2a) Does it have differential effects by social class?

1.2b) Does it have differential effects by school SES composition?

2.1) What is the average effect of FAST on intergenerational closure

2.2) Does the effect of FAST differ by prior level of intergenerational closure?

3.1) How large are social class gaps in child development outcomes in the absence of targeted family engagement efforts?

3.2) How large are social class gaps in intergenerational closure?

3.3) How large would social class gaps in children's mental health be…

3.3a) If all parents were completely socially isolated?

3.3b) If all parents maximally socially connected?

3.4a) How large would social class gaps in children's mental health be if we were to implement FAST…

3.4a) In all schools?

3.4b) In high poverty schools?

Data and Methods

I use two sources of data to explore the research questions in this study. To address research questions 1.1-1.2, I analyze data generated from the Early Childhood Longitudinal Study - Kindergarten Cohort (National Center for Education Statistics 2002), a nationally representative sample of children enrolled in kindergarten during the 1998-1999 school year. To address research questions 2.1-2.2, I analyze data generated from the Children, Families, and Schools project, a randomized study of the causal effects of social capital on child outcomes (Gamoran et al. 2012). Finally, to address research questions 3.1-3.4, I draw from these two sets of analyses using estimates from the experiment with patterns of behavior across the nationally representative sample of schools to evaluate the promise of intergenerational closure for reducing social class inequality in early mental health and academic skills.

Early Childhood Longitudinal Study-Kindergarten Cohort

The Early Childhood Longitudinal Study - Kindergarten Cohort (ECLS-K) is a nationally representative survey of children who were kindergartners in the US in 1998. These data provide information on about 21,000 students within approximately 1,000 schools, describing the learning environments of children, including a wide range of family, school, community, and individual variables that affect children's early success in school.

Sample Weights

ECLS-K employed a complex multistage probability sample design. The primary sampling units were geographic areas (counties or groups of counties), the second stage units were schools sampled within these geographic areas, and the third stage units were kindergarteners sampled within schools (NCES 2009). Within schools, two race/ethnicity-based sampling strata were formed in each school because one of the study's goals was to oversample Asian or Pacific Islander students. Within each stratum, students were selected using equal probability systematic sampling. The analyses are weighted to account for differential probabilities of selection at each sampling stage and for the effects of non-response. I use a cross-sectional weight designed for analyses drawing from the spring of 1st grade school administrator survey, child assessment, parent survey, and teacher survey (National Center for Education Statistics 2002). The use of this weight produces estimates that are representative of the population of first grade children enrolled in public schools in the school year 1999-2000 (NCES 2009: 1-2).

Analytic Sample

I analyze the kindergarten–eighth grade (K–8) full sample public-use data file, focusing on three rounds of data collection: the fall and spring of kindergarten and the spring of first grade. This full sample data file can be used for within-year analyses of any round of data collection from kindergarten through eighth grade, and it also can be used for any combination of cross-year analyses (NCES 2009). School-based parent networks are embedded in particular school environments, conditions of which can either facilitate network building or act as barriers, particularly for disadvantaged groups. Data about the school environment is drawn from school administrator surveys, which were collected in the spring of 1999. I first restrict the sample to public schools. The student sample is restricted to students observed within public schools with valid school administrative surveys (N=11,437 of 13,259 surveyed 1st graders in 1,043 public schools). I further restrict the student sample to include students for whom there are valid data from interviews with parents in the fall of K and spring of K and 1st grade, teacher surveys in the spring of K and spring of 1st grade, valid child assessments in the spring of K and spring of 1st grade, and a valid sampling weight, yielding a child sample size of 7,935 in 834 schools.

Missing Data

Excluding cases with missing information on independent variables further reduces the student sample size to 5,246 students and school sample size from 834 to 748. To avoid the loss of students and schools using listwise deletion, I use multiple imputation with chained equations (MICE). MICE fills in missing values for variables iteratively using a sequences of univariate imputation methods with fully conditional specification of prediction equations (White et al. 2011). The imputation method is iterative, meaning it first estimates the imputation model using both the observed data and the imputed data from the previous iteration. It then draws new imputed values form the resulting distributions. I use the 50th iteration for subsequent imputations to avoid atypical initial iterations. Each set of analyses is conducted on five imputed data sets and combined using Rubin's rules (1987)). There are no substantively significant differences in the means or standard deviations of model variables between the complete case sample and the imputed samples (not shown). After MI procedure to fill in item missingness, I also exclude an additional 99 students who are missing values for any of the seven outcome variables. The final analytic sample includes 7,836 students in 833 schools. The minimum number of students per school is 1 (in 176 schools) and the maximum is 13.5. The average is between 5 and 6 students per school.

Key Measures

Intergenerational Closure

School-based parent social networks benefit children because they aid in information flow, social control, and parental monitoring; help parents enforce a common set of expectations and norms through sanctions and rewards; and provides parents and children with mutual trust, discipline reinforcement, and support within a community based at the school (Coleman et al. 1982; Coleman 1988; Coleman 1990; Carbonaro 1998). I measure whether parents are connected to a school-based parent social network using the following item self-reported by the parent: "About how many parents of children in your child's class do you talk with regularly, either in person or on the phone?" Parents were not given a set of response categories (i.e., responses were open-ended); however, the interviewer was instructed to ensure that the response did not exceed 40.

Child Outcomes

I operationalize mental well-being as children's psychosocial characteristics that affect their engagement with others and their schoolwork. I measure mental well-being using first grade teacher survey items adapted from the Social Skills Rating System (Gresham and Elliot 1990). The SSRS is considered to be a reliable, valid measure of children's social development (Evaluation 2011). I examine two dimensions of mental well-being: internalizing behaviors: anxiety, loneliness, self-esteem, and sadness, and externalizing behaviors: respect for others, temper, anger, impulsivity, sensitivity, and disruptiveness. Each item ranges from 1 to 4 (1= Never exhibits behavior; to 4= Very often exhibits behavior). The scale scores are calculated as the mean of the scale items. Higher values indicate more problems.

Moderating Variables

Family Social Class. Inequality by social class is a central concern of this study. Social class shapes individuals' life chances, and its effects extend across a number of spheres in social life: identity, education, politics, health, and family (Lareau and Conley 2010). Social class encompasses opportunities and limitations for families and children, more so than income or education level alone. I use information on parents' educational, occupational, and poverty status to code students into one of three mutually exclusive and exhaustive categories indicating their family's social class: poor, working class, and students are coded poor if their household income is below the federal poverty line (reported by ECLS-K), regardless of parents' education levels and job positions. They are coded working class if both parents have less than a bachelor's degree and do not work in an executive, administrative, or managerial position and their household income is above the poverty line. Students are coded as middle/upper-class if either parent has a bachelor's degree or higher or works in an executive, administrative, or managerial position and their household income is above the poverty line.

These social class categories meaningfully distinguish families in terms of poverty status, education, and occupation. While there is variation within social class categories, these distinctions matter for families in terms of whom they know, the social and economic resources they bring to bear when raising children, and shared everyday experiences that are masked by continuous measures of financial resources, like income or socioeconomic status. As Freeman and Condron (2011) argue, when using continuous measures, researchers often distinguish social classes by invoking arbitrary cutoff points to categorize families as “high SES” and “medium-low SES,” for example. The approach taken here, which follows Freeman and Condron, specifies theoretically meaningful boundaries between social classes rather than arbitrary groupings based on a continuous measure.

School Socioeconomic Composition. I measure the socioeconomic composition of schools as the percentage of the student population eligible for free lunch. I created a dummy variable to indicate whether a school is a “high poverty” school. I categorize schools as high poverty according to where they would fall if ranked, as is done in the US each year.[2] In the ECLS-K, schools with about 50% or more students who are eligible for free lunch are considered high poverty schools according to this categorization (66% of schools in the analytic sample).

Children, Families, and Schools Project

The Children, Families, and Schools project is an experimental field study of families with first-graders in San Antonio, Texas and Phoenix, Arizona. The study was a cluster-randomized design wherein 26 schools (half in each city) were randomly assigned to receive a family engagement program called Families and Schools Together (discussed below), and the other 26 schools served as comparisons. All families with first graders were invited to participate in the study. Approximately 3,100 families consented (60% of the targeted population).

Intervention: Families and Schools Together

[2] States calculate which schools are “high” poverty by ranking schools according to poverty rate, and schools in the highest quartile are categorized as “high poverty” schools.

Families and Schools Together (FAST) is a popular school-based program designed to improve child outcomes by building strong relationships among families, teachers, and peers (McDonald & Frey 1999; Families and Schools Together, Inc. 2015). Recognized by the US Department of Education (1998) and the Office of Juvenile Justice and Delinquency Prevention (2006) as an exemplary evidence-based program, FAST is also ranked as a top program in the National Registry of Effective Prevention Programs of the U.S. Substance Abuse and Mental Health Services Administration based on four recently completed randomized controlled trials of the intervention (Schinke, Brounstein, & Gardner 2002; Substance Abuse and Mental Health Services Administration 2012). Currently, FAST is implemented in 46 states and 13 countries.

The FAST program sets the stage for the emergence of social capital by building a sense of group membership and belonging, repeated and reciprocated social exchange, and the adoption of shared values, each of which has been identified by Portes (1998) as a source of social capital. I provide a brief description of the key components of FAST here. More details about the FAST program components and their connection to these sources of social capital can be found in a recent qualitative study of the emergence of social capital using the CFS data by Shoji and colleagues (2014).

In the FAST program, families meet weekly for eight weeks and then monthly for two years. The program is multi-faceted, designed to strengthen bonds between and among families with children at the same school. “FAST Nights” consist of twelve core activities, designed on the basis of family systems theory, social-ecological theory, family therapy techniques, delinquency prevention strategies, and research on group dynamics and community development (McDonalds, Billingham, Conrad, Morgan, & Payton, 1997). These components structure interaction specifically to promote social bonding. Activities include participatory music, a family meal, family games, and a parent support group called "Parent Time" (for an in-depth description of the program components, see Kratochwill, McDonald, Levin, Bear-Tibbetts, & Demaray, 2004).

Overall, participation in FAST creates meaningful shared experiences at school. The shared experiences are intended to foster trust, mutual obligations, and shared norms that promote collective efficacy and parent involvement in children's education. Relationships among parents targeted during Parent Time, which consists of parent-led discussions both one-on-one and then as a larger group. During Parent Time, parents discuss matters related to their lives, often centered on their children and the school. This program component provides opportunities for open communication and shared problem solving within a respectful environment, engendering *responsive communication* (communication in which the listener reacts readily and with interest and enthusiasm) and *reciprocal communication* (communication characterized by give and take). The shared experiences and open communication set the stage for reciprocated exchanges, shared values, and a sense of group membership among parents (Shoji et al. 2014), three important sources of social capital (Portes 1998).

Analytic Sample

Overall, 3,084 families participated in the study, just under 60% of the targeted populations, with nearly identical rates of participation in FAST and comparison schools. The analysis draws data from two surveys: pre- and post-treatment surveys of parents. While 99% of parents responded to the pre-treatment survey, about 65% of parents returned surveys during the follow-up. Attrition from the study was non-random:

response rates were higher among parents from comparison schools (69.5%) than FAST schools (61.7%). Within comparison schools but not treatment schools, missing a parent posttest survey was more likely for students who were male (p-value < 0.10), Hispanic (p-value < 0.05), or qualified for free or reduced-price lunch (p-value < 0.10). In both FAST and comparison schools, students missing parent posttest surveys also had lower average pre-treatment social capital (p-value < 0.05). To account for these differences, non-response weights are used to adjust the follow-up parent sample so that it represents the full population of consented children, and I control for pre-treatment measures of social capital, child gender, race/ethnicity, and lunch status in all models. The final analytic sample size is 1,873.

Key Measures

Intergenerational Closure

Intergenerational closure is measured slightly differently in the CFS than in the ECLS-K. In the CFS study the question wording is as follows: "How many parents of your child's friends at this school do you know?" with response categories "0", "1", "2", … "six or more." The question wording in the ECLS-K is slightly different: "About how many parents of children in your child's class do you talk with regularly, either in person or on the phone?" Parents were not given a set of response categories (i.e., responses were open-ended). The open-ended question in the ECLS-K allowed for more variability in the responses. To improve compatibility I impose a ceiling of six or more for the ECLS-K measure.

Methods

RQ1: To address whether intergenerational closure is causally related to child outcomes, I estimate a multi-level random intercept model, weighting each observation by their generalized propensity score. I developed a theoretically motivated propensity score model predicting the number of other parents that parents report knowing at the school to bolster the causal interpretation of the results.

Propensity Score Equation.

I follow the approach described in Hirano and Imbens (2004) and Guardabascio and Ventura (2014) for propensity score matching with continuous treatments. The approach utilizes the residuals from a generalized linear model, which accommodates continuous and non-normally distributed distribution functions of the treatment variable, to generate a generalized propensity score (GPS). I use a normal distribution for the treatment, intergenerational closure, given the covariates, estimated by ordinary least squares regression.

$$T|X \sim N(B_0 + B_1'X, \sigma)$$

The estimated GPS is calculated as

$$R = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{1}{2\sigma}(T - \mathcal{B}_0 - \mathcal{B}_1'X)\right)$$

Unlike in more traditional propensity score models, where the "treatment" is dichotomous, the propensity score in this analysis, $R = r(T, X)$, is defined as the conditional density of the treatment given the covariates, T is the observed treatment, and X is the vector of the observed covariates. The GPS has a balancing property similar to the 'classic' propensity score, in that individuals within the same strata of the GPS should be identical in terms of their observable characteristics, independent of their level of treatment (Hirano and Imbens 2004). Just as in the binary treatment, adjusting for the

GPS theoretically removes all bias associated with differences in the observed covariates.[3]

I evaluated the distribution of the generalized propensity score evaluated at the representative point of three treatment intervals (0-1 parents, 2-3 parents, and 4 or more parents). The region of common support across treatment intervals is small (not shown). This is mainly due to the lack of support in the right tail for the third treatment interval. A conventional propensity score matching approach would be inappropriate in this case, so instead I include the generalized propensity score by weighting each observation by their propensity score.[4]

RQ2: I estimate multi-level random-intercept regression models of the causal effect of FAST on parent social capital, first across all families and schools, and then by prior levels of intergenerational closure.

RQ3: The analyses of the potential impact of intergenerational closure on social class inequality in child outcomes involve Monte Carlo simulations where I predict child development outcomes for middle class, working class, and poor families in multiple artificial samples (Adkins and Gade 2012). The goal is to show how social class inequality in child development changes under different assumptions about the distribution of intergenerational closure, which reflect different counterfactual scenarios

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[3] I included a total of 30 theoretically-relevant covariates in the analysis in order to estimate the propensity scores for levels of intergenerational closure. Tests of statistical difference in the conditional mean of the pre-treatment variables given the generalized propensity score show significant differences between units across three treatment group intervals. This means that there is decisive evidence against the balancing property of the GPS. To control for these differences, I include measures of covariates that demonstrate an imbalance in the model predicting child outcomes.

[4] Because observations are already weighted with respect to their sampling probability, I compute a single weight by multiplying the GPS by the sampling weight (Dugoff, Schuler, and Stuart 2014).

(described below). Generally, the simulations proceed in 4 steps, *separately for each social class* (i.e., poor, working class, and middle class families).

1. Estimate the effect of intergenerational closure in the ECLS-K data using a propensity score weighted multi-level random intercept model of the effect of intergenerational closure on child outcomes.[5] This model is assumed to be the “true” model, which means it is the model that generated the observed data in the ECLS-K.

2. Based on the parameters from the “true” model, generate 1,000 artificial samples.

$$E(y') = \hat{\beta}_0 + \hat{\beta}_1(IC) + u \,, \; N \sim (0,1) \qquad (1)$$

In Equation 1, $E(y')$ represents the simulated child outcome score as a function of two estimated parameters: $\hat{\beta}_0$ (intercept) and $\hat{\beta}_1$ (effect of intergenerational closure), and a normally distributed error term, u. The error takes into account the fact that child outcomes vary for reasons other than differences in intergenerational closure. The weighted effect of intergenerational closure, $\hat{\beta}_1$, is assumed to be orthogonal to the error term because of the propensity score adjustment in Step 1.

3. Regress observed intergenerational closure (IC) on the simulated outcome y':

$$y' = \beta_0 + \beta_1(IC) + \varepsilon \qquad (2)$$

4. Estimate the marginal effect of intergenerational closure at different points in the distribution, depending on the counterfactual scenario under consideration and

[5] Because of the loss of data using complete cases, I use multiple imputation to fill in missing values for item-level missingness on covariates used to predict the propensity score weight. The estimates from this step are averaged across five multiply imputed data sets.

compare the results of the simulations across social classes. First, I simulate predicted outcomes scores for children with intergenerational closure values of "0," for each social class. The average outcome at this level of intergenerational closure reflects what would be expected if all families were socially isolated. Second, I simulate predicted outcome scores for children with intergenerational closure of value "6," for each social class. The average outcome at this level of intergenerational closure reflects what would be expected if all families were maximally connected. The difference in gaps, i.e., the change in gaps between a world where all parents are socially isolated and a world where all parents are maximally connected, is interpreted as *the potential impact* of intergenerational closure for reducing social class inequality in child outcomes. Third, I fix the value of intergenerational closure for each family to reflect the effect of FAST. I compare the counterfactual social class gaps assuming all families attend schools that offer family engagement programs like FAST to the observed social class gaps, which represent "business as usual." The difference in gaps, i.e., the change in gaps between what was observed in the ECLS-K and a world where all schools offer family engagement programs like FAST, is interpreted as the influence of intergenerational closure due to the implementation of family engagement programs, or *the real-world impact* of intergenerational closure. This impact is considered under two policy approaches. The first approach reflects a broad implementation of family engagement programs (i.e., social class gaps are based on changes in intergenerational closure in all schools). The second approach reflects a more targeted policy, wherein family engagement programs are only implemented in high poverty schools (i.e., social class gaps are based on changes in intergenerational closure for families in high poverty schools).

Results

RQ 1.1. Causal Effects of Intergenerational Closure

Table 1 shows that intergenerational closure has a statistically significant effect on internalizing and externalizing behavioral problems in the unweighted models. The evidence from propensity score weighted models suggests that the association between intergenerational closure and externalizing problem behaviors is driven by selection mechanisms that are correlated with externalizing behaviors. Comparing the unweighted and weighted columns in Table 1 shows that the size of the linear regression coefficient is reduced in the weighted models, and the association is no longer statistically significant. In contrast, the results suggest the association between intergenerational closure and internalizing behaviors is robust to adjusting for the propensity score; children with more socially connected parents tend to have lower internalizing problem behaviors (-0.037, $p<0.001$).

RQ 1.2a. Differential Effects of Intergenerational Closure by Family Social Class

There is some evidence that the effect of intergenerational closure differs for families by family social class. Table 2 presents the results of fully interactive models of the effect of intergenerational closure run for separate samples: poor, working, and middle class children. The results suggest that reductions in internalizing behaviors may be limited to working class (-0.05, $p<0.01$) and middle class children (-0.03, $p<0.05$).

RQ 1.2b. Differential Effects of IC by School Socioeconomic Composition

There is suggestive evidence that intergenerational closure is less effective for reducing internalizing problem behaviors in high poverty schools, and that the positive influence of intergenerational closure is mainly concentrated in more advantaged schools, net of within-school individual-level differences in social class. Figure 2 is a plot of the predicted internalizing problem behavior score by level of intergenerational closure for schools where no students are eligible for free lunch ("no poverty schools") and schools where all students are eligible for free lunch ("high poverty schools"). The graph shows that internalizing problems decrease as level of intergenerational closure increases for "no poverty" schools by about 5% of a standard deviation per additional parent ($p<0.001$), but there is no difference in internalizing behavior across the distribution of intergenerational closure in "high poverty" schools.

RQ 2.1. Effect of FAST on Post-treatment IC

The next stage of the analysis is to examine the impact of a family engagement program on intergenerational closure. This analysis gives us a sense of how much we can influence parent social networks using a high quality, widely available family engagement program designed to build social capital. Table 3 shows the overall effect of the program, FAST, on post-treatment intergenerational closure. The average effect of FAST on intergenerational closure is 0.506 ($p<0.001$). This means that parents in FAST schools know 0.506 more parents on average than parents in comparison schools.

RQ 2.2. Inequality in the Effect of FAST on Post-Treatment IC

To assess the impact of FAST for parents who are initially socially isolated compared to parents with more social connections, I tested an interaction of FAST with prior family-level intergenerational closure (Table 4). The effect of FAST is smaller for families who initially scored higher on the measure of intergenerational closure (coef = -0.069, $p<0.05$). This suggests that FAST has a compensatory effect for families who are relatively socially isolated at the start of the study. Table 5 shows a summary of the results of the impact of FAST on intergenerational closure by prior score. The effects range from 0.71 (for parents who did not know any other parents prior to the intervention) to 0.29 (for parents who knew 6 or more parents prior to the intervention).

RQ 3.1. Inequality in children's mental health

The final stage of the analysis is to examine social class inequality in mental health and intergenerational closure. Table 6 offers strong evidence of significant social class gaps in children's mental health problems, net of a set of sociodemographic characteristics of families and schools and children's prior scores in the spring of kindergarten. Generally, the gaps are larger when comparing middle class and poor families than when comparing middle class and working class families. Compared with children from middle class families, children from poor families score higher on measures of internalizing problem behaviors (0.18, $p<0.001$). Compared with children from middle class families, children from working class families score higher on measures of internalizing problem behaviors (0.09, $p<0.01$) and externalizing problem behaviors (0.06, $p<0.01$).[6]

The evidence that school socioeconomic disadvantage negatively impacts children's development is weaker. The percent of the student body eligible for free-lunch programs is not associated with either measure of children's mental health.

RQ 3.2. Inequality in IC

[6] Coefficients are in standard deviation units.

Parental networks differ by social class, and the disadvantage is greater for poor families than for working class families. Table 7 shows significant social class inequality in intergenerational closure. Compared middle class parents, working class parents know 0.27 fewer parents on average ($p<0.001$), and poor parents know 0.48 fewer parents on average ($p<0.001$).

The size of the social class gaps help to put the experimental effect of FAST into context: parents with children in FAST schools knew 0.506 more parents than parents with children in comparison schools ($p<0.001$). Given the size of the social class gaps, it appears the FAST effect is considerable. Furthermore, the effect of FAST is particularly large for families who are initially socially isolated, which as the ECLS-K data suggest are more likely to be working class families or families living in poverty.

RQ 3.3. The potential influence of IC

In order to evaluate the *potential impact* of intergenerational closure on social class inequality in children's mental health, I examine two different counterfactual scenarios: one in which all families are socially isolated and another in which all families are maximally connected. Table 8 displays the predicted mean standardized score for each child outcome across simulated samples. On the left side of the table, predicted means are presented separately for each social class: middle class, working class, and poor. The right side of the table presents social class gaps and their standard errors (i.e., differences comparing average predicted mean scores between middle class and working class or poor children). Panel A represents average outcomes across simulated samples in the "socially isolated" counterfactual, and Panel B represents average outcomes across simulated samples in the "maximally connected" counterfactual.

Comparing panels A and B shows that intergenerational closure has the potential benefit all children, regardless of their social class background. Middle class children whose parents are socially isolated score 0.45 standard deviations higher on the internalizing behaviors scale than children whose parents are well-connected. The difference for working class children is 0.29 standard deviations, and for poor children is 0.14 standard deviations. The pattern is somewhat different for externalizing behaviors: middle class children whose parents are social isolated score 0.43 standard deviations higher on the externalizing behaviors scale than children whose parents are well-connected. The difference for working class children is 0.10 standard deviations. The effect is much larger for poor children, whose externalizing behaviors are reduced by 0.71 standard deviations across the counterfactual conditions. Who benefits the most (children from middle class, working class, or poor backgrounds) depends on the child development domain being considered. Thus, children from middle class families benefit most in terms of reducing internalizing problem behaviors, while children from poor families benefit the most in terms of reducing externalizing problem behaviors.

The consequences of intergenerational closure for social class inequality are not straightforward. For both internalizing and externalizing behaviors, intergenerational closure worsens inequality between working class and middle class families. For internalizing behaviors, intergenerational closure worsens inequality between middle class and poor children (-0.26 to -0.58 standard deviations). However, intergenerational closure narrows the gap between middle class and poor families in externalizing problem behaviors from -0.36 standard deviations to -0.08 standard deviations.

RQ 3.4. The influence of IC due to the effect of family engagement programs

In order to evaluate the *real-world impact* of intergenerational closure on social class inequality, I examine three alternative counterfactual scenarios: the first represents “business as usual” (Panel C in Table 8) and the second and third represent two scenarios in which schools offer family engagement programs: one in which intergenerational closure is manipulated in all schools (Panel D) and the other in which intergenerational closure is manipulated in high poverty schools only (Panel E).

Table 8 displays the predicted means and standard deviations for each child outcome across simulated samples. Overall, the results are much more modest when considering the real-world impact relative to the potential impact of intergenerational closure: comparing “Business as usual” to the counterfactual where FAST is implemented in all schools. The effect of family engagement programs in all schools for middle class children for internalizing behaviors is 4% of a standard deviation and for externalizing behaviors is 5% of a standard deviation. The effect for working class children for internalizing behaviors is 2% of a standard deviation, and there is no effect for externalizing behaviors. The effect for poor children ranges for internalizing behaviors is 1% of a standard deviation and for externalizing behaviors is 5% of a standard deviation.

The implications for social class inequality are similarly subdued, despite incorporating differential effects based on prior levels of intergenerational closure, which, because of the distribution of prior levels of intergenerational closure by social class, were *larger* for families from working class and impoverished backgrounds. The gap in internalizing behaviors between middle class and working class families is essentially the same comparing Panel C to Panel D, and the gap in externalizing behaviors worsens by

3% of a standard deviation. The gap in internalizing behaviors between middle class and poor families is worsened by 3% of a standard deviation, and the gap in externalizing behaviors is narrowed by 3% of a standard deviation.

Comparing Panel C and Panel E shows that, when FAST is only implemented in high poverty schools, the impact of intergenerational closure is negligible for each social class, and social class inequality is substantively unchanged.

Summary of Results

There are significant social class gaps in early childhood mental health. Working class families and families living in poverty are also disadvantaged in terms of intergenerational closure. In simulated samples, I show that increases in intergenerational closure have the *potential* to benefit all children, although the implications for social class inequality in child development outcomes are mixed. The results also show that when we consider actual changes in intergenerational closure of a family engagement program, the extent to which policy can affect levels of intergenerational closure enough to meet its potential may be limited. Although FAST effects are large enough to overcome average differences between middle class, working class, and poor families, the effects of a policy promoting family engagement programs appear to have minimal if any impact on children's mental health overall, and social class inequality in outcomes more specifically.

Discussion

This study evaluates the promise of parent social networks and the social capital within them for reducing social class inequality in mental health in early childhood. I find for a nationally representative sample of first graders and their families intergenerational closure has a causal effect internalizing behaviors but not externalizing behaviors.

I tackle one potential policy solution to counter the strong hold of social class: family engagement programs, particularly programs designed to build strong parent social networks. Although not all programs highlight relationships among parents as a key component of their program, the family engagement program examined in this study, Families and Schools Together (FAST), puts as a central focus the potential benefits of building strong networks of parents. I show that FAST successfully builds social capital in a sample of 52 high poverty, majority Hispanic schools. Furthermore, the program successfully engages and builds social capital the most for families that are initially socially isolated. This social capital has the potential to confer significant social resources for both parents and children in the form of information, normative climates, collective efficacy, and social-emotional support and advice.

These two pieces of the puzzle – the impact of intergenerational closure and the potential for family engagement programs to meaningfully increase intergenerational closure – are not enough to understand the potential impact of policies promoting family engagement programs on social class inequality in children's mental health. I address this issue in a simulation, where I show that implementing FAST in schools would do little to improve child outcomes generally and its impact on social class inequality would be negligible, even if the program targeted high poverty schools.

Figures and Tables

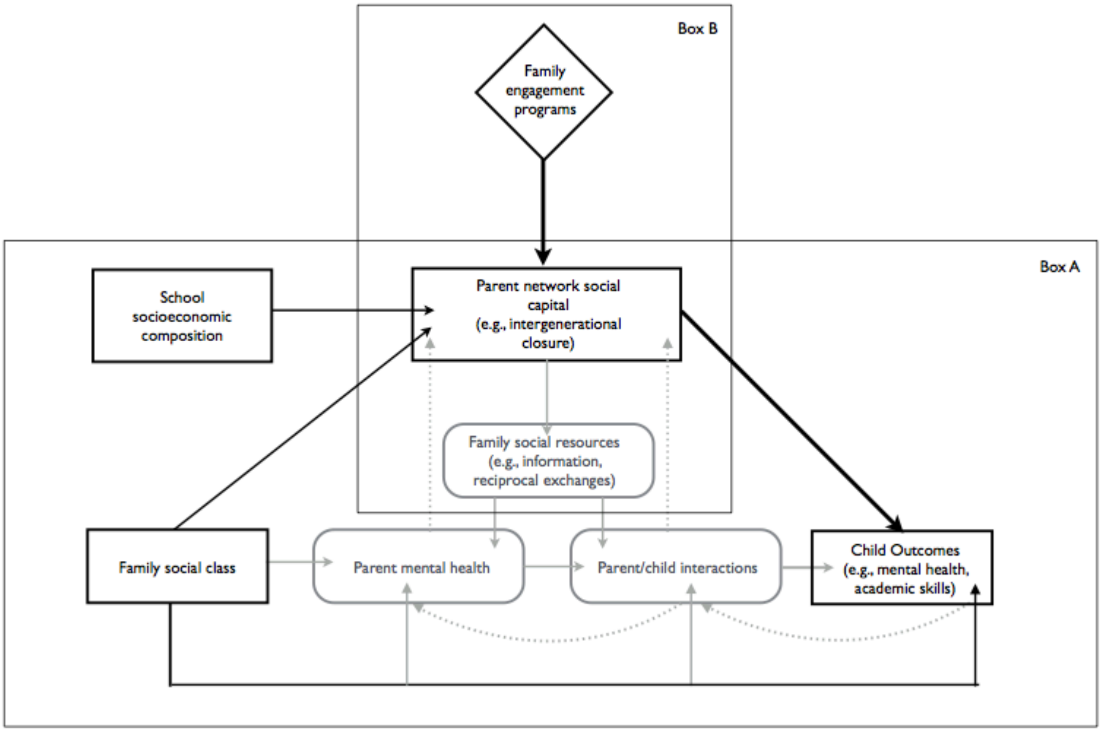

Figure 1. Conceptual Model

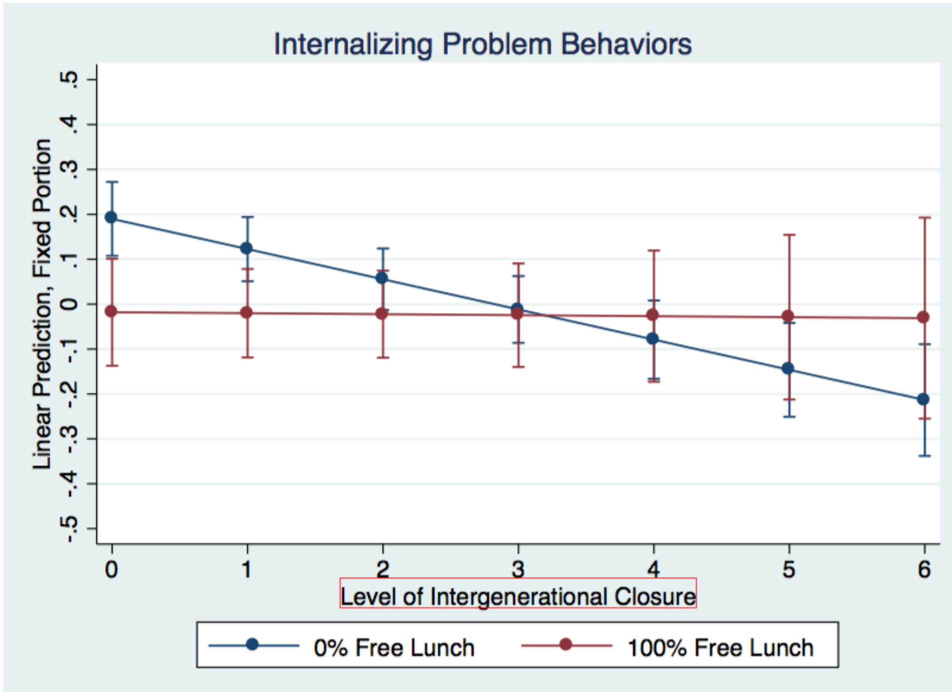

Figure 2. Interaction of Intergenerational Closure and % Free Lunch on Predicted Internalizing Problem Behaviors

Table 1. Effect of Intergenerational Closure on Child Development Outcomes

	Unweighted	Weighted
Internalizing Problem Behaviors	-0.026***	-0.037***
	(0.007)	(0.009)
Externalizing Problem Behaviors	-0.014*	-0.006
	(0.006)	(0.009)

Notes: ~ p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Standard Errors in Parentheses; All models weighted to account for sampling probability

Table 2. Effect of Intergenerational Closure on Child Development for Poor, Working Class, and Middle Class Children

				95% Confidence Interval		
Internalizing problems	N	Constant	Beta	LB	UB	P-value
Poor	1521	0.666	-0.013	-0.074	0.049	0.683
Working Class	3719	0.216	-0.046	-0.076	-0.016	0.003
Middle Class	2952	0.313	-0.032	-0.059	-0.006	0.017

Externalizing problems	N	Constant	Beta	LB	UB	P-value
Poor	1521	-1.233	-0.043	-0.096	0.009	0.105
Working Class	3719	-0.853	0.008	-0.017	0.033	0.520
Middle Class	2952	-0.505	-0.001	-0.024	0.023	0.958

Table 3. Effect of FAST on Post-treatment Family-level Intergenerational Closure

Fixed Effects	Coefficient	se	95% Conf. Interval
FAST	0.506***	0.082	0.344 – 0.668
Pre-treatment Family-level Intergenerational Closure	0.606***	0.017	0.573 – 0.638
Pre-treatment School-level Intergenerational Closure, Standardized	0.087	0.047	-0.006 – 0.181
Random Effects	**Estimate**	**se**	**95% Conf. Interval**
Intercept Variance	0.017	0.016	0.002 – 0.109
Residual Variance	2.728	0.109	2.521 – 2.951
Observations	**N**		
Students	1,991		
Schools	52		

Notes: Significance tests are two-tailed: * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$. Estimated means and standard errors adjusted for clustering of students within schools. Model controls study design effects: School district, study cohort, and season.

Table 4. Effect of FAST on Post-treatment Family-level Intergenerational Closure by Pre-treatment Family- and School-level Intergenerational Closure

Fixed Effects	Coefficient	se	95% Conf. Interval
FAST	0.712***	0.132	0.452 – 0.971
Pre-treatment Family-level Parent Social Capital	0.638***	0.024	0.593 – 0.684
Pre-treatment School-level Parent Social Capital	0.009	0.063	-0.115 – 0.134
FAST*Pre-treatment Family-level Parent Social Capital	-0.069*	0.032	-0.131 – -0.008
FAST*Pre-treatment School-level Parent Social Capital	0.162	0.098	-0.031 – 0.355

Random Effects	Estimate	se	95% Conf. Interval
Intercept Variance	0.014	0.016	0.001 – 0.127
Residual Variance	2.722	0.110	2.514 – 2.947

Observations	N
Students	1,991
Schools	52

Notes: Significance tests are two-tailed: * $p < 0.05$, ** $p < 0.01$, and *** $p < 0.001$. Estimated means and standard errors adjusted for clustering of students within schools. Model controls study design effects: School district, study cohort, and season.

Table 5. FAST Effects on Intergenerational Closure by Pre-treatment Intergenerational Closure

		95% CI	
Number of Parents	Point Estimate	LB	UB
0	0.71	0.45	0.97
1	0.64	0.38	0.90
2	0.57	0.31	0.83
3	0.50	0.24	0.76
4	0.43	0.17	0.69
5	0.36	0.10	0.62
6	0.29	0.03	0.55

Table 6. Social Class Gaps in Child Development Outcomes

	Mental Health	
Family Social Class	Internalizing Behavior Problems	Externalizing Behavior Problems
Working Class	0.090*	0.060*
	(0.04)	(0.02)
Poor	0.188**	0.058
	(0.07)	(0.05)
School Socioeconomic Composition		
% Free Lunch	-0.000	0.000
	(0.00)	(0.00)

Notes: ~ p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Standard Errors in Parentheses; Models control for socio-demographic characteristics of families and schools and children's prior scores measured in the spring of Kindergarten.

Table 7. Social Class Inequality in Intergenerational Closure

	Intergenerational Closure
Working class	-0.267***
	(0.07)
Poor	-0.483***
	(0.10)
% Free lunch, Standardized	-0.004
	(0.00)
N	9081

Notes: ~ p<0.10, * p<0.05, ** p<0.01, *** p<0.001; Standard Errors in Parentheses; Model controls for child, family, and school demographic characteristics.

Table 8. Estimated Average Child Outcomes in Simulated Samples

	Family Social Class			Middle Class vs. Working Class		Middle Class vs. Poor	
Panel A. Socially Isolated	Middle Class	Working Class	Poor	Difference	Standard Error	Difference	Standard Error
Internalizing	0.01	0.16	0.27	-0.15	0.007	-0.26	0.007
Externalizing	0.01	-0.01	0.38	0.02	0.006	-0.36	0.006
Panel B. Maximally Connected							
Internalizing	-0.44	-0.13	0.13	-0.31	0.011	-0.58	0.010
Externalizing	-0.42	-0.09	-0.33	-0.33	0.009	-0.08	0.010
Panel C. Business as Usual							
Internalizing	-0.15	0.06	0.22	-0.21	0.005	-0.37	0.005
Externalizing	-0.13	-0.04	0.13	-0.10	0.005	-0.27	0.005
Panel D. Impact of FAST in All Schools							
Internalizing	-0.19	0.03	0.21	-0.22	0.005	-0.40	0.005
Externalizing	-0.18	-0.04	0.06	-0.13	0.005	-0.24	0.005
Panel E. Impact of FAST in High Poverty Schools							
Internalizing	-0.16	0.05	0.22	-0.21	0.005	-0.38	0.005
Externalizing	-0.14	-0.04	0.11	-0.11	0.005	-0.26	0.005

Notes: T-tests of social class differences in outcomes are all statistically significant at the p<0.01 level.

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