Predicting Variation in Responsiveness

to the Family Check-Up in Early Childhood:

A Mixture Model Approach

by

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A Thesis Presented in Partial Fulfillment
of the Requirements for the Degree
Master of Arts

Approved March 2016 by the
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ARIZONA STATE UNIVERSITY

May 2016

ABSTRACT

The present study applied latent class analysis to a family-centered prevention trial in early childhood to identify subgroups of families with differential responsiveness to the Family Check-up (FCU) intervention. The sample included 731 families of 2-year-olds randomized to the FCU or control and followed through age five with yearly follow up assessments (Dishion et al., 2014; Shaw et al., 2015). A two-step mixture model was used to examine whether specific constellations of family characteristics at age 2 (baseline) were related to intervention response at age 3, 4, and 5. The first step empirically identified latent classes of families based on a variety of demographic and adjustment variables selected on the basis of previous research on predictors of response to the FCU and parent training in general, as well as on the clinical observations of FCU implementers. The second step modeled the effect of the FCU on longitudinal change in children's problem behavior in each of the empirically derived latent classes. Results suggested a five-class solution, where a significant intervention effect of moderate-to-large size was observed in one of the five classes. The families within the responsive class were characterized by child neglect, legal problems, and mental health issues. Pairwise comparisons revealed that the intervention effect was significantly greater in this class of families than in two other classes that were generally less at risk for the development of disruptive behavior problems, and post hoc analyses partially supported these results. Thus, results indicated that the FCU was most successful in reducing child problem behavior in the highly distressed group of families. We conclude by discussing the potential practical utility of these results and emphasizing the need for future research to evaluate this approach's predictive accuracy.

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CHAPTER 1

INTRODUCTION

Early-onset conduct problems entail substantial costs to society and to individuals. It has long been known that 5% of early-starting individuals commit 50% of crimes (Offord, Boyle, & Racine, 1991), and those children and teenagers who are affected by early-onset conduct problems often demonstrate impaired health, happiness, occupational outcomes, and family relationships as adults (Dishion & Patterson, 2006). Thankfully, these negative outcomes can be reduced through early intervention to prevent growth in conduct problems (O'Connell, Boat, & Warner, 2009). Although several interventions have been proven efficacious, it is also clear that they are not sufficient to eliminate impairment for all children. Thus, "What works for whom?" is an important question: effective and efficient implementation of services requires understanding variation in outcomes associate with families in specific conditions (Borkovec & Bauer, 1982; Paul, 1967). The present study seeks to answer this question for one such intervention, the Family Check-Up.

An Ecological Perspective on the Development of Antisocial Behavior

Interventions for early-onset conduct behavior generally rely on an ecological conception of the development of antisocial behavior. This model frames children's behavior as an adaptive response to the particular environmental context—family, peers, teachers, neighborhood, epoch—in which they are situated. For example, being oppositional or aggressive might be adaptive in the presence of conciliatory parenting practices or dangerous peers. Indeed, a long tradition of research has implicated family, peer, and neighborhood factors in the development of antisocial behavior (Dishion & Patterson, 2006).

Family factors are perhaps the most well-understood determinants of antisocial behavior. Poor parenting practices are one of the strongest predictors of adolescent antisocial behavior (Loeber & Dishion, 1983). Similarly, the presence of maternal depression during early childhood increases the risk of problem behavior during middle childhood (Shaw, Gilliom, Ingoldsby, & Nagin, 2003). Siblings can also contribute to antisocial tendencies via dynamics such as modeling, sibling collusion, and sibling-based deviancy training (Dishion & Patterson, 2006).

Peer dynamics are also predictive of behavior problems. These factors are active as early as preschool, when peer selection and reinforcement are already predictive of rates of aggression (Snyder et al., 1996). Transitioning to middle childhood, much work has demonstrated pathways from social rejection to aggressive behavior (Dishion & Patterson, 2006). By adolescence, peer effects are even more salient—antisocial teenagers tend to have self-selected into social groups of antisocial peers. Indeed, deviant peer involvement and antisocial behavior are strongly correlated in adolescent samples (Patterson & Dishion, 1985).

Finally, neighborhood context can also promote or discourage antisocial behavior. Community disadvantage might lead to antisocial behavior via exposure to violence and victimization, as well as interaction with peers who have themselves committed violent acts or been victimized (Ingoldsby & Shaw, 2002; Yoshikawa, Lawrence, & Beardslee, 2012). Review of the empirical literature confirms modest cross-sectional and longitudinal relationships between neighborhood danger, exposure to violence, victimization, and antisocial behavior during childhood (Ingoldsby & Shaw, 2002).

Parenting Interventions for Early-Onset Conduct Problems

Given the well-established role of parenting in the development of antisocial behavior, parenting practices are an obvious target for intervention to prevent early-onset conduct problems. Indeed, behavioral parent training is one of the most empirically-supported interventions for child and adolescent mental health problem and is the core component of many of the existing psychosocial programs (Weisz & Kazdin, 2010). Many of these interventions have been developed specifically to reduce early-onset conduct problems and have robust positive effects. A recent review of 55 studies of the effects of early parent training on antisocial behavior and delinquency found a weighted effect size of 0.35 (Piquero, Farrington, Welsh, Tremblay, & Jennings, 2009). Moreover, results indicated that these programs also reduce crime and delinquency into adolescence and adulthood (Piquero et al., 2009).

However, these evidence-based interventions are not without limitations. First, they often entail many sessions over an extended time period and thus can be quite expensive to implement and demanding of parents' time. Second, they typically adhere to a heavily structured curriculum, irrespective of the specific deficits present in a given family. Finally, most do not explicitly address parents' motivation to change parenting practices. This may be a particularly serious limitation in prevention (i.e., non-indicated) samples, wherein families may not yet be sufficiently distressed that parents feel the effort to engage in parent training is worthwhile or necessary, thus missing a critical opportunity to improve their parenting to prevent an emerging yet serious problem behavior trajectory.

The Family Check-Up: A Public Health Intervention Model

The Family Check-Up (FCU) is an evidence-based approach to reducing the incidence of conduct problems that was developed to address some of the limitations of the traditional parent training model. The FCU is a brief preventive intervention based on motivational interviewing and modeled after the Drinker's Check-Up (Miller & Rollnick, 2002) that seeks to motivate parents to engage in services that improve the quality of their parenting practices. This framework was originally developed in the context of preventing substance use and abuse during adolescence (Dishion & Kavanagh, 2003). Early results suggested providing the FCU during middle school resulted in reduced rates of initiation of substance use from 6^{th} to 9^{th} grade (Dishion, Kavanagh, Schneiger, Nelson, & Kaufman, 2002). Importantly, the FCU was effective even within the high-risk subset of this sample, with reductions in substance use mediated by improvements in parental monitoring (Dishion, Nelson, & Kavanagh, 2003). Later results indicated that engagement in the FCU during middle school resulted in reduced growth in substance use across adolescence and into young adulthood, as well as reduced symptoms of substance abuse in young adulthood (Connell, Dishion, Yasui, & Kavanagh, 2007). In addition to these positive effects on substance use, the FCU has been found to result in significant improvements in long-term patterns of antisocial behavior (Van Ryzin, Stormshak, & Dishion, 2012), risky sexual behavior (Caruthers, Ryzin, & Dishion, 2014), depressive symptoms (Connell & Dishion, 2008), and academic functioning (Stormshak, Connell, & Dishion, 2009).

Given the success of the FCU framework during early adolescence, another line of research has sought to extend it to the early childhood period. At this age, the intervention aims to prevent growth in aggressive and oppositional behavior that may lead to more severe conduct problems. A pilot study with 120 indigent families with male 2-year olds seeking food stamp and health services (Shaw, Dishion, Supplee, Gardner, & Arnds, 2006) indicated that providing the FCU at age two resulted in reduced disruptive behavior and greater maternal involvement at ages three and four. This pilot study was followed by a much larger, multisite trial (Dishion et al., 2008) that found substantial reductions in growth in children's externalizing behavior when their caregivers were offered annual FCUs over the same age range. Follow-up of this sample into primary school (Dishion et al., 2014) has indicated that these reductions continue through age 5, and that teacher ratings at age 7.5 show significant effects of the FCU on reducing aggressive and oppositional behavior in the school context. These improvements may be related to improved inhibitory control: children receiving the FCU displayed faster growth in inhibitory control from age 2 to 7.5 than did those children that did not receive the intervention (Chang, Shaw, Dishion, Gardner, & Wilson, 2014). In addition to improved school behavior, the FCU also had indirect positive impacts on academic achievement at age 5 and 7.5, as indicated by scores on the Woodcock-Johnson III Academic Skills composite (Brennan et al., 2013). These indirect effects were mediated by improved parenting practices during early childhood, consistent with the FCU's rationale.

However, these studies also make it clear that the FCU is not sufficient to eliminate problems in all families. For example, in the multisite early childhood trial, 27% of the intervention-group children remained in the clinical range on age 5 parent ratings of externalizing behavior, as did 23% on age 8 teacher ratings (Achenbach & Rescorla, 2001). Moreover, the intent-to-treat effect on teacher ratings was modest (d = 0.17), and minority families were less likely to engage in the FCU at every opportunity (Dishion et al., 2014). These results suggest it may be important to identify families less likely to respond to the intervention. This would facilitate the adaptation of the FCU to meet the unique needs of these specific subpopulations less likely to respond, as well as the rerouting of families for whom the FCU is insufficient to more extensive, higher-dose interventions. In present formulations of the FCU, dosing and tailoring decisions (i.e., which topics to cover, in what fashion) are left as a joint decision of the therapist and client; the results of a careful moderation analysis may suggest a more systematic approach to adapting the intervention to each particular family's needs.

Potential Moderators of Response to the FCU

Moderation analysis provides a means of examining whether the level of one variable, the moderator, affects the relationship between two other variables (Aiken & West, 1991). In the context of response to the FCU, moderators would be variables that influence the intervention's effects on various outcomes. Indeed, previous studies have examined processes that might enhance or limit FCU effects. Gardner et al. (2009) tested potential moderators of the effects of the FCU on growth in externalizing problems during early childhood. These analyses identified teen parent status and single parenthood as family characteristics that limited intervention effectiveness, with large moderating effects. Surprisingly, *lower* parental education was associated with *larger* intervention effects—Cohen's d was 1.17 in less educated families but just 0.15 in highly educated families. In another analysis of this same sample, Shaw et al. (2015) examined the moderating effects of families' neighborhoods on FCU effects into late elementary school. Intervention effects were observed only for those experiencing moderate levels of neighborhood deprivation, rather than extreme. However, FCU effects *were* observed for families living in poor neighborhoods when parents improved the quality of their parent-child interaction during early childhood, suggesting the moderating effect of neighborhood is not a simple one.

Although there are only two moderation analyses specific to the Family Check-Up, there have been many studies of moderation of other parent training-based interventions. Reyno and McGrath (2006) conducted a meta-analysis of moderators of parent training efficacy and identified 31 studies examining 15 different moderators. They found lower family income, more severe child behavior, higher maternal psychopathology, lower parental education, and more barriers to treatment to have medium to large negative effects (r ~ .30-.50) on treatment efficacy. Greater number of siblings, single parenthood, and higher maternal depression had smaller negative effects (r ~ .20).

Lundahl, Risser, and Lovejoy (2006) also meta-analyzed moderators of parent training efficacy, but examined fewer moderators in a wider literature base (63 studies). Despite the fact that only three studies were included in both reviews (i.e., there was little overlap), these authors concurred with Reyno and McGrath's (2006) finding that lower socioeconomic status and single parenthood limited treatment efficacy. However, they reached the opposite conclusion regarding severity of child behavior problem: families with children in the clinical range received *greater* effects of parent training relative to families with children in the nonclinical range.

As discussion of these two reviews has indicated, the FCU-specific moderation findings do not map perfectly onto those from the more general parent training literature. In addition, the two reviews sometimes reached contradicting conclusions (e.g., regarding severity of child behavior), and both conducted statistical tests that indicated substantial heterogeneity in the included studies. Together, these results suggest that moderation of response to the FCU may be more nuanced and warrant a different analytic approach.

Most existing studies examine moderation of intervention effects using a variable-centered approach, modeling covariation among variables in what is presumed to be a homogenous sample. Indeed, all of the findings reviewed above used this method, typically by including a series of treatment × moderator interaction terms in a multiple regression equation. However, it may be that a particular *constellation* of family conditions presents a context that affects response to the intervention: this variable-centered approach might fail to detect this effect if no *single variable* emerges as a predictor.

A Person-Centered Approach to Moderation of Response to Intervention

This limitation can be addressed via person-centered analytic approaches that seek to separate a heterogenous sample into more homogeneous latent subpopulations (B. Muthén & Muthén, 2000). Although these models have become popular tools to assess response to intervention (e.g., growth mixture modeling), they also offer an alternative perspective on *moderation* of intervention response (Lanza & Rhoades, 2013). Herman et al. (2007) provide an early example of this methodology in modeling latent profiles of co-occuring symptomology (e.g., anxiety, oppositionality) in the Treatment for Adolescents With Depression Study (TADS). Although the descriptive results of the mixture analysis was the primary focus of the paper, they also examined treatment × class interactions to determine if the latent profiles moderated intervention effectiveness. None of these interactions were significant, perhaps owing to the modest sample size (N=423, partitioned into five classes).

More recently, Cooper and Lanza (2014) applied a person-centered moderation methodology to the Head Start Impact Study (3-year-old cohort, N=2,449), conducting a latent class analysis on the sample and then examining intervention effects in each latent class. Their results provide a more compelling illustration of the ability of this quantitative approach to illuminate the critical nuances determining intervention effects. Five latent classes were identified, two of which experienced mostly positive intervention effects, two of which experienced no intervention effects, and even one of which possibly experienced iatrogenic effects. The most robust effects were observed for a class characterized as married, English-language learners with lower education, whereas Head Start appeared to have little effect in a class characterized as married, lower risk families. These results painted a very different picture than would have a traditional, variable-centered method, illustrating the potential of the person-centered approach to clarify response to intervention.

Present Study

A person-centered approach might complement traditional means of identifying families more or less likely to respond to the FCU and thus allow implementers to preserve finite resources and ensure the receipt of appropriate services. Families likely to respond to the FCU could be targeted for engagement, while families unlikely to respond to the FCU could be directed to more suitable services. The present study applied this methodology to the Early Steps Multisite Trial, a large randomized, controlled trial of the FCU in early childhood (Dishion et al., 2014; Shaw et al., 2015). A two-step mixture model was used to examine whether specific constellations of family characteristics at age 2 (baseline) were related to intervention response at age 3, 4, and 5. The first step empirically identified latent classes of families based on a variety of demographic and adjustment variables selected on the basis of previous research on predictors of response to the FCU and parent training in general, as well as on the clinical observations of FCU implementers. The second step modeled the effect of the FCU on longitudinal change in children's problem behavior in each of the empirically derived latent classes.

CHAPTER 2

METHODS

Participants

731 at-risk families were recruited from the Woman, Infants, and Children (WIC) Nutritional Supplement program in three different cities: Eugene, OR, Charlottseville, VA, and Pittsburgh, PA. Parents were invited to participate if they had a two-year old child and possessed two of the three following risk factors for future behavior problems: current child behavior problems, family problems (e.g., maternal depression), and sociodemographic risk. Primary caregivers were almost universally mothers (16 fathers). Racial and ethnic background was as follows: 50% European American, 28% African American, 13% biracial, 9% other, and 13% Hispanic. Sixty six percent of the sample had an income below $20,000 and 41% had a high school diploma. See Dishion et al. (2008) for more detail about the recruiting process and sample characteristics.

Design

Families were randomly assigned to either a control or intervention condition when the child was age 2. Those in the intervention condition gained access to services implementing the Family Check-Up (FCU) model. The FCU comprised three sessions:

1. *Initial interview*. The interviewer explored parent concerns and stage of change and encouraged parents to participate in an in-home assessment of family functioning.
2. *Assessment session*. The interviewer went to the home and videotaped the parent and child while they engaged in various tasks selected to evaluate parent-child interactions.

3. *Feedback session*. The interviewer provided feedback based on the assessment while seeking to promote reflection on behavior change and on potential engagement in further intervention services.

See Dishion and Kavanagh (2003) for more detail about the FCU intervention. After completing the FCU, parents were able to engage in as-desired follow-up parenting support services such as parent training (Everyday Parenting Curriculum; Dishion, Stormshak, & Kavanagh, 2011).

Intervention-assigned families were re-contacted annually at ages 3, 4, and 5 and were offered the same FCU plus follow-up services package. We defined engagement in the intervention as requiring completion of (at least) the FCU feedback session. By this standard, 77% of families engaged in the intervention at age two, 62% at age three, 60% at age four, and 55% at age five. Detailed assessments were conducted for families at each of these ages regardless of intervention status.

Baseline Measures

Ten different variables were collected at baseline (age 2) and entered as indicators in a latent class analysis. Descriptives for all ten appear in Table 1.

Child problem behavior. Primary caregiver completed the Child Behavior Checklist (Achenbach & Rescorla, 2001). The raw total score on the Externalizing subscale was used as a broadband measure of disruptive behavior. Alpha reliability of this scale was 0.86.

Family income. Primary caregiver reported monthly household income (including child support and other financial aid) on an approximately linear categorical scale where answers ranged from “$415 or less” (coded as 1) to “$7,500 or more” (coded as 13). This variable was treated as continuous for these analyses.

Number of children in household. Primary caregiver reported the number of children currently living in the household.

Parental depression. Primary caregiver reported on personal depression on the Center for Epidemiologic Studies Depression scale (CES-D, Radloff, 1977). Alpha reliability of this scale was 0.76.

Child gender. Child gender was coded as 0=female, 1=male.

Parental education. Primary caregiver reported his or her educational history. This was used to form a categorical variable scored as a 1 (less than high school), 2 (high school graduate through partial college), and 3 (junior college degree or more).

Single parent status. Primary caregiver reported whether he or she currently had a live-in partner; this formed a binary indicator of single parent status.

Household law problems. Primary caregiver reported whether persons living in the home had had trouble with the law since the child was born; this formed a binary indicator of household law problems.

Household child abuse. Primary caregiver reported whether persons living in the home had been reported for child abuse since the child was born; this formed a binary indicator of household child abuse.

Household mental health treatment received. Primary caregiver reported whether persons living in the home had been treated by a mental health professional since the child was born; this formed a binary indicator of household mental health problems.

Dependent Measure

Parent ratings of aggressive/oppositional behavior. Primary caregiver completed the CBCL at age 2, 3, 4, and 5. Eight items describing aggressive/oppositional behavior were present on the CBCL at all four ages and were averaged to create a score ranging from 0 to 2 (0 = not true; 1 = somewhat true; 2 = very true) for each child at each age. Alpha reliability of this score was 0.71 at age two, 0.75 at age three, 0.78 at age four, and 0.80 at age five. Descriptives at each age appear in Table 1.

Analytic Plan

All analyses were conducted in MPLUS 7.3 (L. K. Muthén & Muthén, 2012). A two-step method was used in order to ensure the model was computationally tractable.

Step 1: latent class analysis. In step 1, a mixture model was fit to identify latent classes of families that might differ in their responsiveness to the intervention. The variables listed above under "Baseline Measures" were all included as indicators of the latent class. Continuous variables were standardized and modeled as normally distributed. The binary variables (e.g., gender, household child abuse) and parental education were all modeled as (ordinal) categorical.

Selecting the number of latent classes in a mixture model remains a subjective process, as various fit statistics perform differently in simulations and often contradict each other (Tein, Coxe, & Cham, 2013). In the present study, we based this decision on the intuitive, theoretical plausibility of the solution and on three fit indices: the sample-adjusted Bayesian Information Criterion (saBIC; Sclove, 1987), the Lo-Mendell-Rubin likelihood ratio test (LMR; Lo, Mendell, & Rubin, 2001), and the bootstrapped Likelihood Ratio Test (BLRT; McLachlan & Peel, 2000). One, two, three, four, five, and six latent class solutions were produced sequentially and the results were evaluated according to these criteria.

Step 2: multiple-groups latent growth model. In step 2, the latent classes identified in step 1 were treated as observed by assigning each family to its most likely class. A multiple-groups latent growth model was then fit within a structural equation modeling framework (Grimm, Ram, & Estabrook, forthcoming). The "groups" were the latent classes from the mixture model and the "growth" was in aggressive and oppositional behavior from age 2 to 5 (CBCL). Following the procedure of Dishion et al. (2014), linear growth was specified. The latent linear slope factor was regressed on intervention status and allowed to vary across the multiple groups in order to evaluate the FCU's effect in each of the latent classes (model depicted in Figure 1). The latent intercept factor was also regressed on intervention status because (despite randomization) there were sometimes large intervention/control differences in baseline child behavior within the smaller classes. The model-estimated intervention effect size in each latent class was computed by multiplying the coefficient relating intervention status to the slope factor by three (the number of time intervals) and dividing the result by the full-sample standard deviation in aggressive and oppositional behavior at baseline (SD = 0.34; Equation 7 in Feingold, 2009, 2015). Finally, in order to examine whether the effect of the FCU differed significantly across latent classes the MODEL CONSTRAINT command was used to conduct a series of pairwise tests of differences in the intervention status coefficient across the classes.

Missing data handling. Baseline family characteristics at age 2 all had less than 2% missing data. Parent ratings of aggressive/oppositional behavior ranged from 0 to

16% missing: age 2 (100%), age 3 (90%), age 4 (85%), and age 5 (84%). At the participant level, 539 of 731 (74%) participants had complete data for all the variables in both steps of the analysis.

We used full-information maximum likelihood (FIML) estimation to address missing data, assuming a Missing at Random (MAR) mechanism. Given the negligible amount of missing data on the baseline family characteristic variables, the latent class analysis was conducted assuming the data to be MAR conditional on only the variables entered into the model. Given the more substantial missing data in the longitudinal ratings of aggressive/oppositional behavior, nine auxiliary variables were included in the latent growth model using the saturated correlates approach (Graham, 2003) in order to enhance the plausibility of the MAR assumption (see Supplementary Material for details).

CHAPTER 3

RESULTS

In order to improve readability and facilitate comparison, all results are presented in tables and figures. Wherever possible, the classes are color-coded across tables and figures.

Step 1: Latent Class Analysis

Fit statistics for the various K-class solutions are presented in Table 2. These suggested a 3-, 4-, or 5-class solution was viable. Adding a fourth class separated a small class of distinct families (class 4 below), and all three fit statistics indicated this addition produced statistical improvement. Adding a fifth class drew from the two largest classes in the 4-class solution to produce a sizeable class (class 5 below) with dramatic differences from all other classes on the categorical indicators. Thus, we settled on a 5-class solution.

The five identified latent classes can be roughly characterized as follows:

- *Class 1 (N=181)*—very high income, low-risk
- *Class 2 (N=105)*—low income, very high maternal depression, high single parenthood
- *Class 3 (N=323)*—low income, high single parenthood, otherwise low-risk
- *Class 4 (N=29)*—high behavior problem, very high number of kids, high neglect, high maternal depression
- *Class 5 (N=93)*—high law problems, very high neglect, extremely high mental health treatment

Note that descriptors such as “low” and “high” are *relative to the rest of the present sample*—for example, the “very high income” of Class 1 corresponded to just $25-30k per year. The exact profile of each of the identified classes across the ten baseline (age 2) family characteristics is depicted in Figure 2 (continuous indicators) and Figure 3 (categorical indicators). Entropy for this solution was 0.74, suggesting there was some uncertainty in the process of assigning individual families to classes (a value of 1 would reflect absolute certainty). The distributions of the estimated probabilities of membership in each class (“posterior probabilities”) were inspected in order to ascertain the source of uncertainty. For classes 1 through 4, membership was relatively certain: more than 50% of the members had estimated posterior probabilities of membership in their respective class of greater than 0.90, and fewer than 25% were below 0.70. For class 5, membership was less certain: only 16% of members had posterior probabilities of greater than 0.90 (*Median* = 0.71, *Interquartile Range* = [0.62, 0.83]).

Step 2: Multiple-Groups Latent Growth Model

We next examined the effects of assignment to the Family Check-Up on growth in aggressive-oppositional behavior within each of these five latent classes. Estimates of effects are reported in Table 3, and the model-estimated trajectories of the intervention and control groups within each latent class are depicted in Figure 4. A significant intent-to-treat effect of randomization to the Family Check-Up was observed in Class 5 (p<.01; d = -0.63), which was characterized by high rates of neglect, legal problems, and mental health issues. Pairwise comparisons indicated that the effect in Class 5 was significantly greater than the effect in either Class 1 (p<.05; d = -0.01), which consisted of high income, low-risk families, or Class 3 (p<.05 ; d = -0.08), which consisted of low income, single-parent families that were otherwise at low risk. Thus, results suggested the effects of random assignment to the FCU were more pronounced in distressed families compared to those characterized as low risk.

Post Hoc **Analysis**

Given the uncertainty for individual latent class membership in the distressed group (Class 5), we next formulated three groups using simplified, researcher-specified definitions based on the pattern of findings revealed in the latent class analysis. These definitions separated the sample into three classes—(A) low-risk, (B) demographic risk, and (C) demographic plus parental mental health risk—on the basis of five of the indicator variables (parental depression, history of mental health treatment, history of legal problems, single parent status, and income). The exact class criteria are presented in Table 4. We then fit the same latent growth model shown in Figure 1 within each of these three researcher-specified classes: results are reported in Table 4 and depicted graphically in Figure 5. Consistent with previous findings, a significant intervention effect was observed only in the class with both demographic and mental health risk (Class C; $p<.01$; $d = -0.56$), and the effect in this class was marginally significantly greater than that in either of the two classes without both types of risk factors (Classes A and B; *p*s<.10; *d*s = -0.15 and -0.04).

CHAPTER 4

DISCUSSION

Five different latent classes of families were identified, and the effect of random assignment to the FCU in early childhood was examined in each. Results indicated the intervention had a moderate-to-large effect size in reducing parent-rated problem behavior in the class of families characterized by high rates of neglect, legal problems, and mental health issues. Pairwise comparisons among the classes indicated the intervention effect was significantly greater in this class of distressed families than in two other classes that were generally less at-risk for the development of disruptive behavior problems. *Post hoc* analyses also indicated a moderating role of mental health issues. We now discuss these results and their implications.

Family Support for Distressed Families with Young Children

Note that this study involved a large group of community families seeking financial support through the WIC program—*not* a group of families seeking FCU services. Within that context, our results suggest that those families with high rates of legal problems, child neglect, and mental health treatment were *more* responsive to the FCU. This finding mirrors those from the earlier, variable-centered analyses of this dataset showing that families with more risk factors benefited more from the intervention (Gardner et al., 2009). This pattern was also seen in recent analyses showing that FCU-based reductions in neglectful parenting were greatest for those families with greater family adversity (Dishion et al., 2015), and that parents with greater perceived parenting stress were considerably more likely to engage in the intervention (Smith et al., under review). The fact that families at relatively low risk (i.e., Classes 1 and 3) did not appear responsive to the FCU in the present study may indicate these children are less likely to develop the problem behavior to be prevented, or are less likely to have the poor parenting practices that can be improved via intervention. Indeed, a desirable feature of any preventive intervention is that it reaches and benefits the most in-need families.

The intervention appeared to be most effective for those families with high rates of child abuse (Classes 4 and 5). In conjunction with recent results indicating the FCU can reduce neglectful parenting during directly-observed parent-child interaction (Dishion et al., 2015), this finding suggests potential utility of the FCU in the child welfare setting. Families at-risk for neglect may benefit from receiving the FCU *before* the child has been removed from the home and more intensive services are needed (Dishion, Forgatch, Chamberlain, & Pelham, in press). Moreover, the FCU could prove useful in reducing the rate of placement failure for children identified as at-risk for disruptions because of problem behavior (Chamberlain et al., 2006).

The Latent-Class-as-Moderator Approach for Prediction

Moderation analysis is useful for understanding intervention processes, but it can also be used to estimate the likelihood a specific family will respond to the intervention. The present model can calculate a predicted effect size of the FCU for each family in the sample. This quantity is of interest because families for whom the predicted effect is quite large could be especially targeted for intervention, while families for whom the predicted effect is quite small could be redirected to other services, monitored prospectively, or left alone. The distribution of predicted effect sizes is displayed in Figure 6, adjusted for uncertainty assigning families to specific classes (i.e., weighted by the posterior probabilities). As indicated, more than 50% of the sample had a predicted effect size that was close to zero. Approximately one-third of the sample had a predicted effect size of “small” or greater ($d > 0.20$), and approximately one-tenth of the sample had a predicted effect size of “medium” or greater ($d > 0.50$). These results suggest that there may be substantial variability in responsiveness to the FCU among families engaged in the WIC program.

This variability in responsiveness to the FCU is an important consideration for real-world implementation. Approximately 50 items are needed to yield all of the baseline characteristic scores that were included in the latent class model (8 individual items, 24 items from the CBCL externalizing subscale, and 20 items from the CES-D). With this information, straightforward arithmetic is needed to produce estimated probabilities of membership in each class and thus a predicted effect size for a specific family. Administration of the items and instantaneous calculation of the predicted effect size could be accomplished via a simple web application. The application could then display a predicted effect size and/or recommended action (e.g., “probably helpful”, “maybe helpful”, “probably not helpful”) that is customized to audience (i.e., parent, therapist, physician). Thus, in fewer than 10 minutes, families could be evaluated for their potential need and responsiveness to a potential FCU, and parents and providers could receive tailored, practical advice.

The implementation outlined above is straightforward, but it is still aspirational. Future work must address several issues. First, the current 50-item assessment could be reduced considerably in length if subsets of CBCL and CES-D items can approximate the predictive value of the full scales (e.g., Andresen, Malmgren, Carter, & Patrick, 1994). A shortened version would be especially useful for broader screening in primary care settings, but further development is needed. Second, the present analyses were conducted using data from a sample of families in WIC demonstrating multiple risk factors for the development of child conduct problems, and thus the prediction model was fit in this context. The extent to which the prediction equation would generalize to populations that are more (e.g., families seeking treatment for behavioral problems) or less (e.g. primary care) at-risk is unknown. Third, and most important, cross-validation of the prediction model is needed to determine its accuracy out of sample (Hastie, Tibshirani, & Friedman, 2009). This entails applying the prediction model to a new sample and examining the correspondence of the predicted effect sizes to the observed effect sizes. At present, we have no guarantee that our predicted effect sizes are accurate; this is obviously of paramount importance.

Limitations

A substantial limitation of the present study is its definition of response to intervention exclusively through parent ratings of aggressive and oppositional behavior. Although this was the primary outcome of the multisite trial, other studies have demonstrated ancillary effects of the FCU in the domains of maternal depression (Shaw, Connell, Dishion, Wilson, & Gardner, 2009), positive parenting (Dishion et al., 2008), teacher rating of problem behavior (Dishion et al., 2014), and inhibitory control (Chang et al., 2014), among others. Thus, families we have presently identified as *not* benefiting from the intervention (e.g., Class 1) may in fact have seen positive effects in one of these other domains. Future work could repeat the present methodology but define response to intervention through a broader, composite measure.

A second substantial limitation is that our analysis conflates assignment to treatment with receipt of treatment. Of those randomly assigned to the intervention condition, 76% completed an FCU at age 2, 69% completed an FCU at age 3, and 70% completed an FCU at age 4 (Dishion et al., 2014). Thus, a specific class of families may herein be identified as not responding (a) because they fail to engage in the FCU or (b) because they do engage in the FCU, but do not benefit from engagement. Since these possibilities imply very different plans of program modification and implementation, future work should disentangle them.

Finally, several limitations stem from our mixture model approach to moderation. First, because the classes vary across all of the baseline characteristics, it is unknown whether the differential effectiveness of the FCU across classes is indeed attributable to discrepancies we identified (i.e., legal problems, neglect, mental health problems). It may be that the differential effectiveness is due to other variables upon which the classes differed. Second, mixture models will identify multiple classes whenever the indicator variables depart substantially from normality (Bauer & Curran, 2003; McLachlan & Peel, 2000), and the specific pattern of the present results is consistent with the expected methodological artifacts (i.e., the classes differ most substantially on the highly skewed variables). This emphasizes the need to avoid reifying the classes and view them instead as a potential predictive tool (Sterba & Bauer, 2010).

Conclusion

The present results used a latent-class-as-moderator approach to identify a class of highly distressed families for whom the effect of the FCU was substantial, as well as to identify non-trivial subsamples for which the effect on problem behavior appears to be limited. Critically, these latent classes were indicated by characteristics of the families at the baseline assessment. If implementers of the FCU can indeed identify non-responsive families *before* initiating the intervention, they can reduce costs and increase efficacy (i.e., be more efficient). Thus, in the prevention context, the classic question of "What works for whom?" might fruitfully be reframed as "What *doesn't* work for whom?" Future work should address the limitations of the present study and seek actionable answers to this question.

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APPENDIX A

TABLES AND FIGURES

Table 1

Descriptives for All Variables

Variable	Control	Intervention	Class 1	Class 2	Class 3	Class 4	Class 5
Number of participants	364	367	181	105	323	29	93
Baseline Variables for Latent Class Analysis							
Parent CBCL externalizing behavior	20.6 (7.0)	20.8 (7.6)	19.4 (6.9)	22.9 (7.4)	19.8 (7.0)	24.8 (9.1)	22.6 (7.0)
Family income	4 [2-5]	4 [2-5]	6 [5-7]	3 [2-4]	3 [2-4]	4 [3-6]	4 [3-4]
Number of children in household	2 [2-3]	2 [2-3]	2 [2-3]	2 [2-3]	2 [1-3]	6 [5-6]	2 [1-3]
Parental depression (CES-D)	14 [9-22]	15 [9-23]	12 [7-18]	35 [31-41]	12 [8-17]	22 [15-29]	14 [10-20]
Parental education	25 / 64 / 11%	22 / 66 / 12%	10 / 68 / 22%	30 / 56 / 13%	33 / 61 / 6%	45 / 55 / 0%	3 / 86 / 11%
Child male	51%	50%	49%	55%	48%	52%	56%
Single parent status	42%	38%	0%	57%	54%	45%	45%
Household law problems	35%	34%	7%	44%	27%	38%	87%
Household child abuse	7%	8%	4%	9%	2%	21%	29%
Household mental health treatment received	39%	38%	40%	44%	17%	45%	100%
Parent Ratings for Growth Model							
Mean score CBCL aggressive/oppositional items at age 2	0.64 (0.32)	0.67 (0.35)	0.61 (0.31)	0.75 (0.34)	0.62 (0.33)	0.81 (0.41)	0.73 (0.34)
Mean score CBCL aggressive/oppositional items at age 3	0.56 (0.35)	0.55 (0.35)	0.48 (0.34)	0.71 (0.37)	0.54 (0.33)	0.57 (0.38)	0.57 (0.32)
Mean score CBCL aggressive/oppositional items at age 4	0.52 (0.35)	0.47 (0.36)	0.45 (0.35)	0.66 (0.43)	0.47 (0.33)	0.58 (0.36)	0.47 (0.28)
Mean score CBCL aggressive/oppositional items at age 5	0.47 (0.36)	0.43 (0.35)	0.40 (0.34)	0.64 (0.37)	0.43 (0.36)	0.42 (0.37)	0.45 (0.32)

Note. Where numbers are followed by brackets, they are in this form: median [25^{th}-75^{th} percentiles]. Where they are followed by parentheses, they are in this form: mean (standard deviation). See Methods section for description of variable measurement scales (e.g., for family income). All figures are complete-case, with Ns per variable as indicated in the Missing Data Handling section.

Table 2

Fit Statistics for Latent Class Analysis Solutions

Fit Indicator	**1-class solution**	**2-class solution**	**3 class-solution**	**4-class solution**	**5-class solution**	**6-class solution**
Sample size-adjusted BIC	13,875	13,676	13,581	13,533	13,506	13,491
Lo-Mendell-Rubin LR test	-	p<.0001	p=.0072	p=.02	p=.06	p>.10
Bootstrapped LR test	-	p<.0001	No convergence	p<.0001	p<.0001	p<.0001
Sizes of classes (*N*s)	731	488, 243	211, 125, 395	388, 109, 205, 29	181, 105, 323, 29, 93	76, 240, 163, 104, 118, 30

Note. BIC = Bayesian Information Criterion, LR = likelihood ratio. The 5-class solution was selected.

Table 3

Parent-Rated Aggressive/Oppositional Behavior: Intervention Effects Within Each Latent Class

Class	**N**	**Est. (SE)**	**Model-Estimated Effect Size**
Class 1 very high income, low-risk	181	-.001 (.014)	*d* = -0.01
Class 2 low income, very high maternal depression, high single parenthood	105	-.034 (.026)	*d* = -0.30
Class 3, low income, high single parenthood, otherwise low-risk	323	-.009 (.014)	*d* = -0.08
Class 4 high behavior problem, very high number of kids, high neglect, high maternal depression	29	-.092 (.075)	*d* = -0.82
Class 5 high law problems, very high neglect, extremely high mental health treatment**	93	-.070 (.026)	*d* = -0.63

Note. Note that descriptors (e.g., low, high) are relative to the rest of the sample. "Est." is the coefficient of latent slope regressed on dummy-coded intervention status (see Figure 1). "Model-Estimated Effect Size" reflects the total effect across age 2 to 5 span, as described in Methods section. Negative effect sizes indicate advantage of intervention over control. Pairwise tests indicated significant differences in effects between class 1 and class 5 (p<.05) and between class 3 and class 5 (p<.05).
$^{\dagger}p$<.10, *p<.05, **p<.01, by z-tests.

Table 4

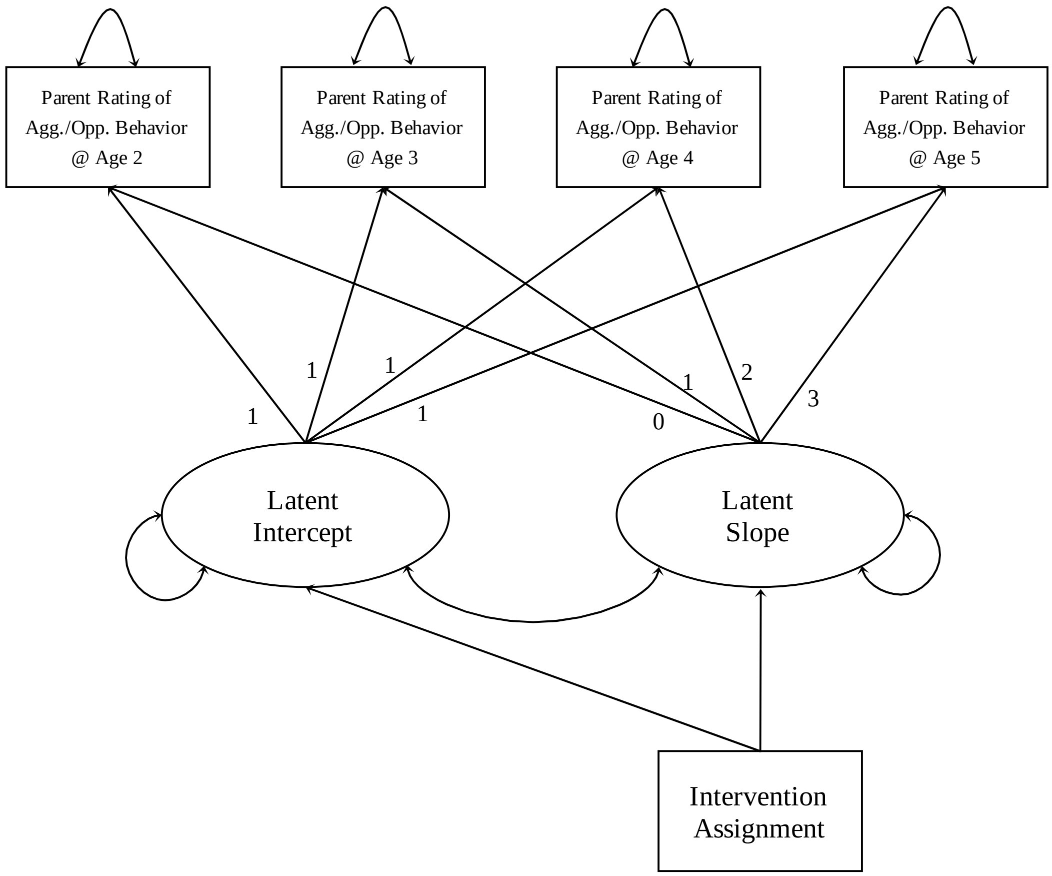
Parent-Rated Aggressive/Oppositional Behavior: Intervention Effects Within Each Researcher-Defined Class

Class	**N**	**Est. (SE)**	**Model-Estimated Effect Size**
Class A low risk Did not meet criteria of either other classes	493	-.017 (.011)	*d* = -0.15
Class B demographic risk Either single parent or lower tercile income (<$1250/mo.), CES-D<=15, neither mental health treatment or legal problems	105	-.005 (.021)	*d* = -0.04
*Class C demographic risk + mental health risk*** Either single parent or lower tercile income (<$1250/mo.), CES-D>15, either or both of mental health treatment or legal problems	133	-.063 (.022)	*d* = -0.56

Note. "Est." is the coefficient of latent slope regressed on dummy-coded intervention status (see Figure 1). "Model-Estimated Effect Size" reflects the total effect across age 2 to 5 span, as described in Methods section. Negative effect sizes indicate advantage of intervention over control. Pairwise tests indicated the effect in Class 3 was nearly significant different from that in Class 1 (p = .054) or Class 2 (p = .055).
$^{\dagger}p<.10$, $^{*}p<.05$, $^{**}p<.01$, by z-tests.

Figure 1

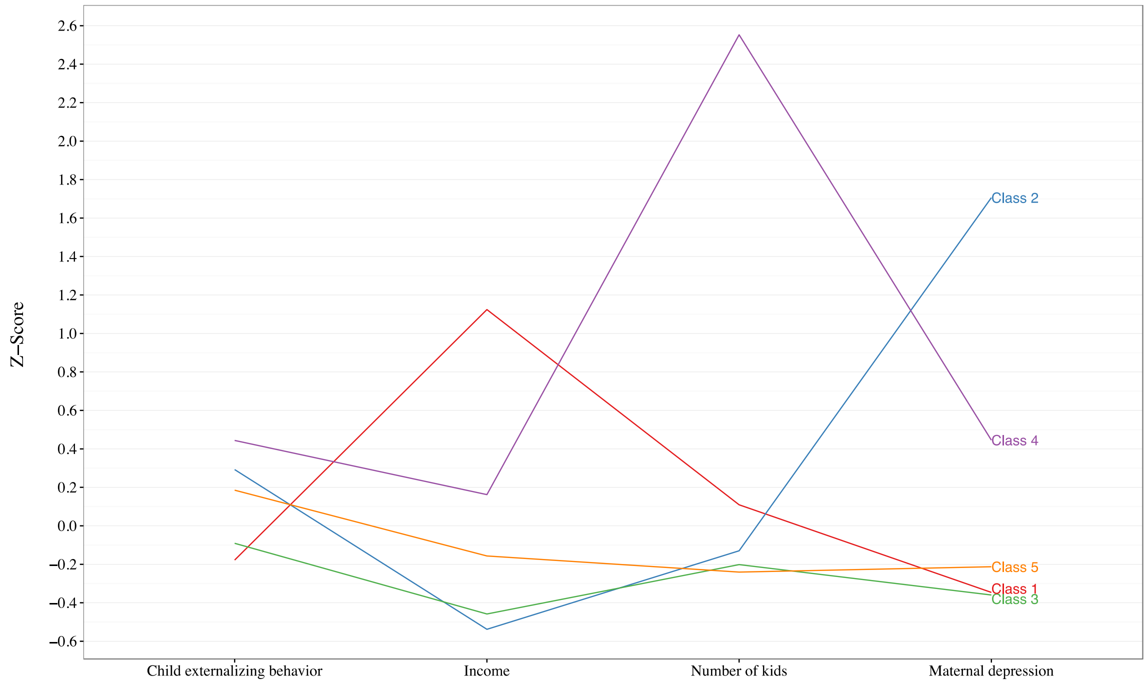
Diagram of Parent-Rated Aggressive/Oppositional Behavior Growth Model Fit Within Each Latent Class



Note. Agg./Opp. = Aggressive and Oppositional behavior. Model was fit within each of the five classes identified, and all free parameters were allowed to vary across classes.

Figure 2

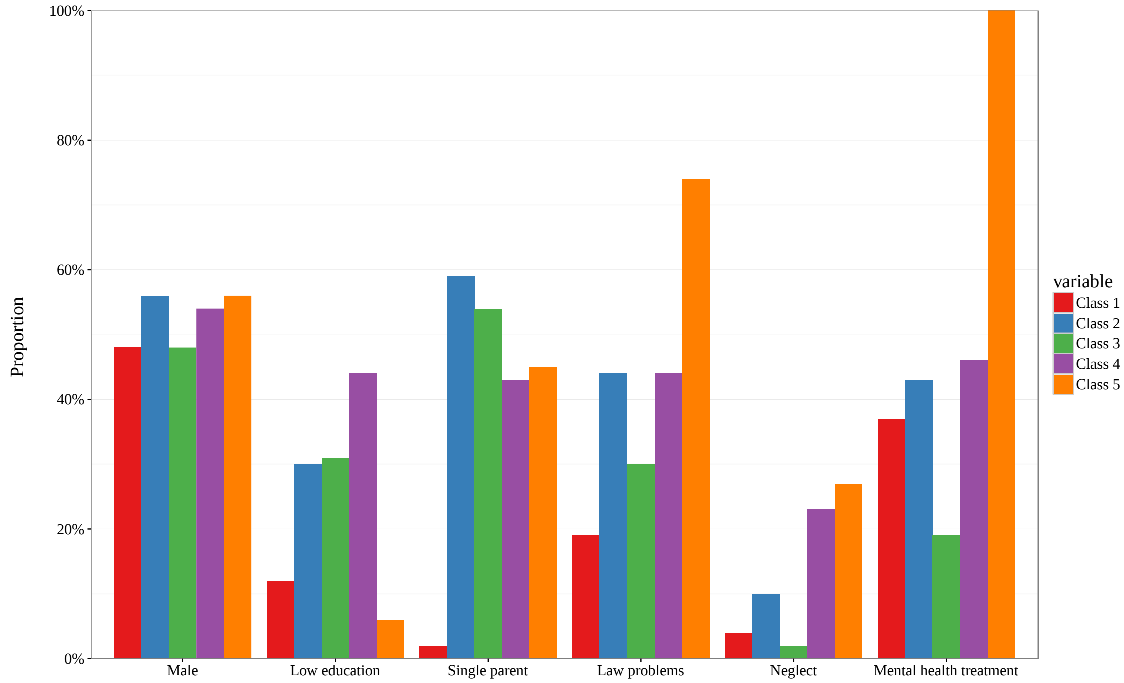
Profile of Latent Classes on Continuous Indicators



Note. Figures calculated based on most likely class membership.

Figure 3

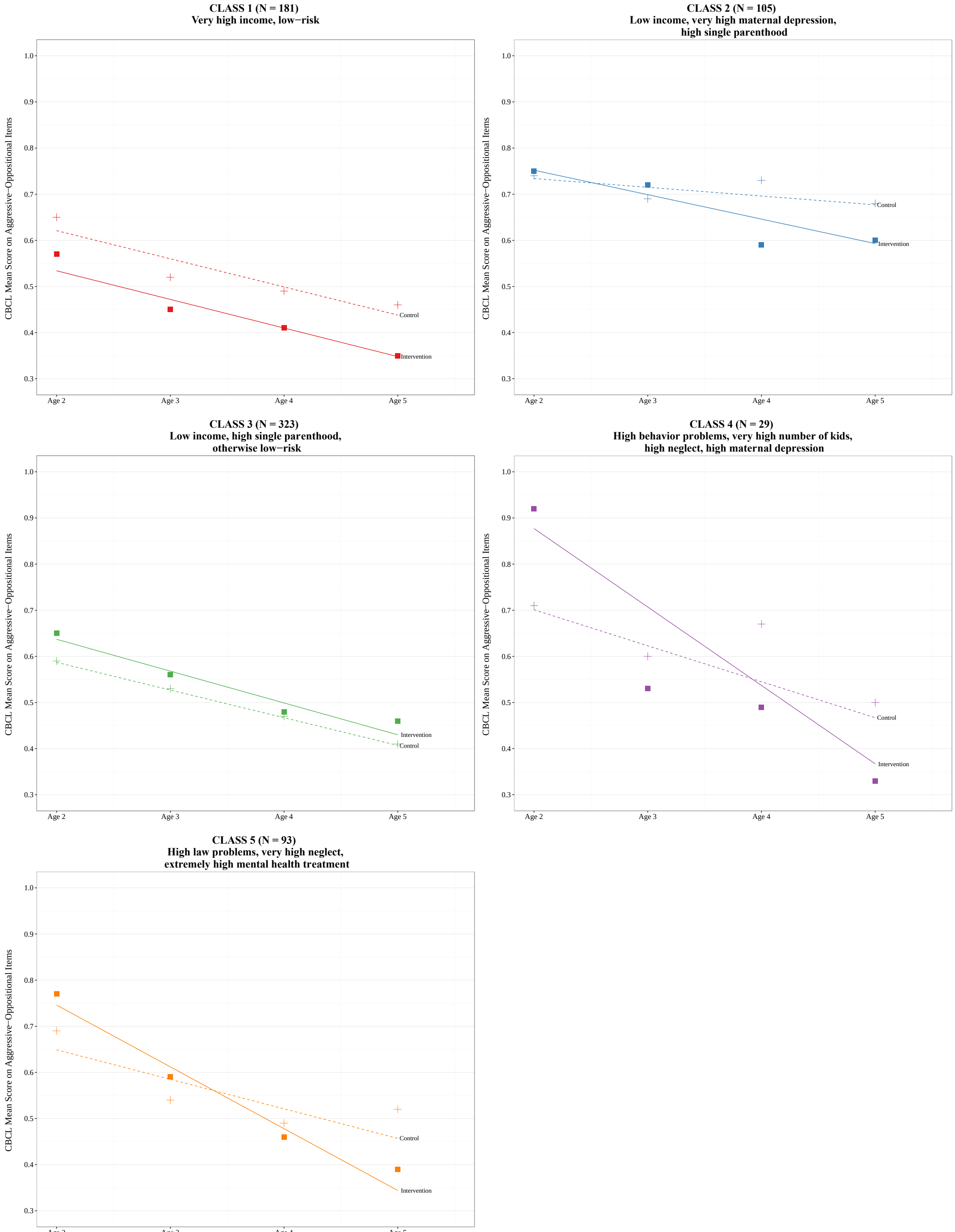
Profile of Latent Classes on Categorical Indicators



Note. Y-axis represents the proportion of each class endorsing the categorical indicators. Figures calculated based on most likely class membership.

Figure 4

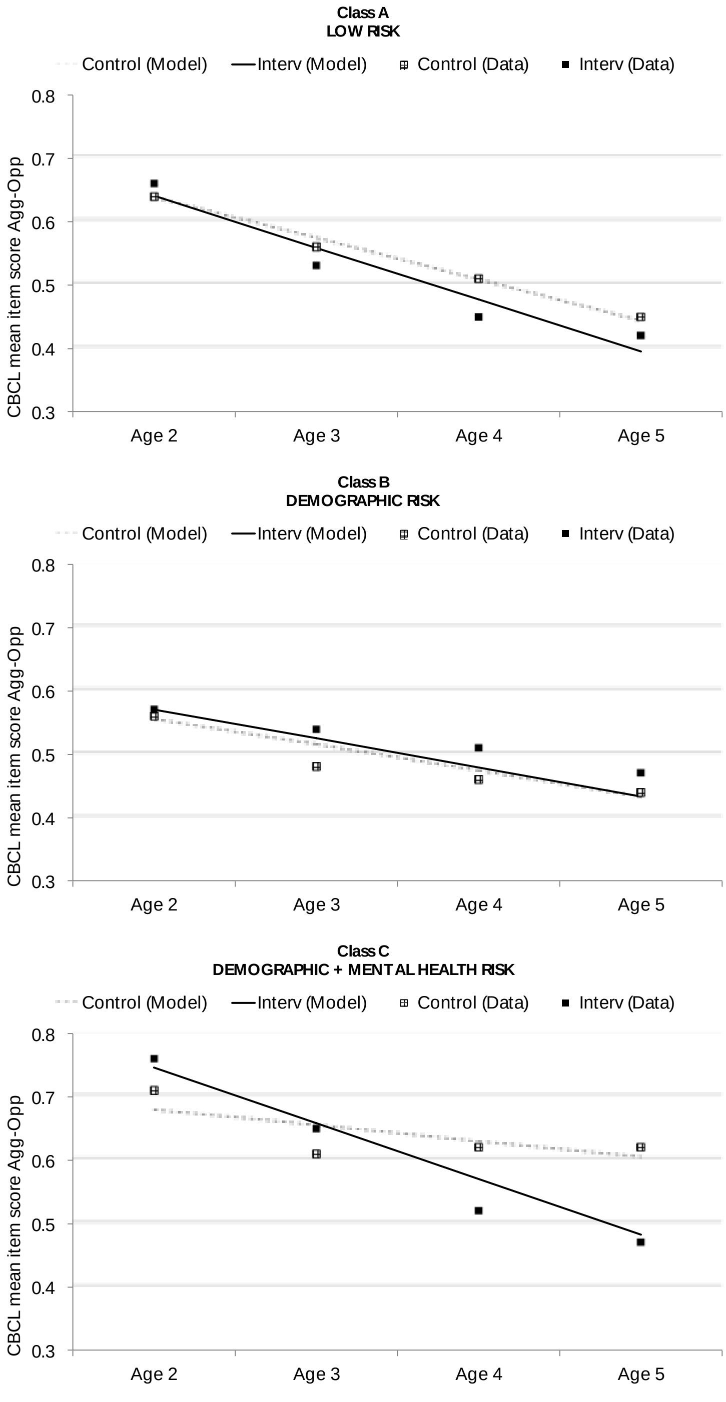
Parent-Rated Aggressive/Oppositional-Behavior: Model-Estimated Growth Curves for Intervention and Control Groups Within Each Latent Class



Note. Lines represent model-estimated growth curves. Points represent the observed means for each group at each age, using only available data (i.e., without missing data handling).

Figure 5

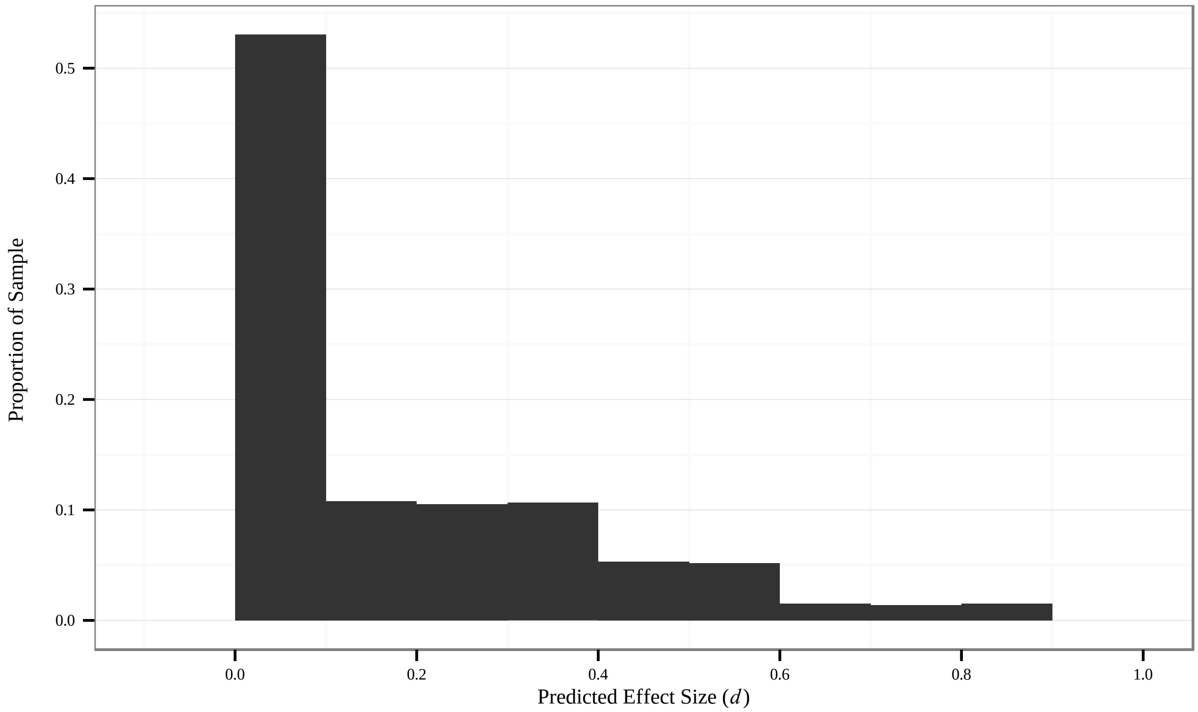
Parent-Rated Aggressive/Oppositional-Behavior: Model-Estimated Growth Curves for Intervention and Control Groups Within Each Researcher-Defined Class



Note. Lines represent model-estimated growth curves. Points represent the observed means for each group at each age, using only available data (i.e., without missing data handling).

Figure 6

Distribution of Predicted Effect Sizes of Assignment to FCU



Note. Histogram of the predicted effect size of random assignment to the FCU. "*d*" is growth-model-estimated Cohen's *d* (positive indicates advantage of intervention condition), and predictions for each family were weighted by that family's posterior probability of membership in each latent class.

APPENDIX B

SUPPLEMENTARY MATERIAL

Auxiliary Variable Selection

The MVA function in SPSS 23.0 was used to identify variables that were highly correlated with missingness on the parent ratings of aggressive/oppositional behavior. Inspection of participation data suggested that dropout was not monotonic, in that some families did not participate for a year or two yet returned to the study for later waves. Thus, approximately 1,000 scores measured at ages 2-5 were assessed for inclusion. This list was narrowed to 55 scores by including only those where the *t*-statistic comparing those missing and not missing the aggressive/oppositional variable was greater than 1.5 at all three ages (i.e., 3, 4, and 5). Nine of these were selected for inclusion in the latent growth model:

1. Age 2: primary caregiver's education level
2. Age 2: gross monthly income including child support and other financial aid
3. Age 2: receiving food stamps (binary)
4. Age 2: receiving financial aid for medical assistance (binary)
5. Age 2: area of family strength is support from extended family (binary)
6. Age 2: in-home visitor's rating of parent involvement
7. Age 2: observer's rating of primary caregiver's monitoring and tracking
8. Age 3: observer's rating of primary caregiver's proactive parenting
9. Age 3: primary caregiver's perception of parenting daily hassles

The variables included possess strong face validity as predictors (both of the missing values and missingness) and include both self-report and direct-observation measures. Most were from the age 2 wave, which might be expected given power considerations for the *t*-test. The latent growth modeling framework already incorporates those measures most predictive of missing aggressive/oppositional ratings: ratings at previous waves.