A Stochastic Dynamic Model of the Mental Health of Children*

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We estimate the parameters of a dynamic multi-period model where parents with one child periodically decide whether their child uses mental health services. In this model, parents receive utility from household consumption and from their child's mental health. Mental health services may improve the child's mental health but may be costly in terms of reduced household consumption and direct disutility. We find that mental health services can slightly improve a child's mental health but that the use of services accounts for a small fraction of the improvement of the mental health of the children in our sample.

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1 Introduction

In this paper, we estimate the structural parameters of a new dynamic model of parental investments in a child's mental health. A good case can be made that a child's mental health is an important component of his or her health and human capital and correspondingly, parents should thoughtfully evaluate the choices that affect the mental health of their children. An example from our data illustrates the importance of the topic: In the six months prior to the first Wave of data, 10% of our sample of children and adolescents had set fire to property. It seems plausible that parents of these children probably wished to correct this behavior as soon as possible. But what choices did parents have? One possibility would have been to wait and hope that the child's mental health naturally improved with time. Alternatively, potentially costly mental health treatments could have been purchased that might have immediately corrected the problem.

Our research seeks to explicitly understand and quantify the value to parents of these options. In our model, parents with one child receive per-period utility from household consumption and their child's stock of mental health. Each period, parents choose whether or not to obtain different combinations of outpatient, inpatient, and/or intensive community-based mental health services for their child. Mental health services may increase their child's stock of mental health, but may be costly to parents in terms of both household consumption and direct disutility. Parents optimally make these decisions until their child turns eighteen years old.

To estimate the parameters of this model, we use panel data that were collected in order to evaluate the Fort Bragg Demonstration, one of the largest and perhaps most influential demonstrations ever conducted in the field of children's mental health services (Bickman et. al. 1995, Office of the United States Surgeon General 1999). The Demonstration tested the "Continuum of Care" philosophy of providing mental health services to children: In addition to providing outpatient and inpatient mental health services, the Demonstration offered "intermediate" mental health services that are, generally speaking, not available elsewhere. The Demonstration also encouraged the use of mental health services by mounting a public relations campaign and providing all services freely. The campaign included beneficiary workshops, briefings with local providers, and targeted media coverage to potential clients via television ads, newspapers on post, fliers distributed to relevant organizations on post, and post bulletins.

Data were collected from a sample of children and youth at Fort Bragg as well as from comparable children and adolescents at two similar posts, Fort Campbell, Kentucky, and Fort Stewart, Georgia. Although the Fort Bragg study is not nationally representative, it offers data on a large sample of users of mental health services, children and adolescents often excluded from or under-represented in national studies of young people. A total of 984 children participated in a longitudinal study that combined data from semi-annual interviews with administrative data on service use, which may be more accurate than self- or parental-report. The service use data are gathered directly from insurance claims at the Comparison sites and a management information system at the Demonstration.

Using a simulated maximum-likelihood procedure, we estimate the structural parameters of our model with a subset of these data. Our working sample contains information on 142 single-child households followed over four waves (two years). The estimation procedure embeds the solution of the parents' dynamic programming problem directly into the likelihood function. The likelihood accounts for the non-random sampling of the data and missing data. Importantly, the likelihood allows for unobserved heterogeneity in the mental health endowment of children, and, unobserved heterogeneity in parental preferences.

Our model closely fits many of the important cross-sectional and time-series aspects of the data, but unfortunately the standard errors on most of our interesting parameters are large. The conclusions we draw build on the fact that our estimates are consistent. Prefacing our conclusions, we find that parents are reluctant to use mental health services due to direct disutility, but these services can slightly improve a child's mental health. We further show that almost all of the improvement of the mental health of children in the estimation sample is due mainly to mean reversion and not the use of mental health services. To understand the impact of the three key aspects of the Demonstration on choices and outcomes, we run counterfactual simulations and find that the effort to promote services altered parents' choices but no aspect of the Demonstration significantly altered the mental health of children, a result that confirms previous assessments of the Demonstration (Bickman 1995). In our final simulation, we check if inpatient services can be safely replaced with intermediate services, as reflects the current thinking among researchers and providers. With this change, we simulate that parents alter their use of services but child outcomes are unaffected.

Although this paper is related to the literature that studies the process by which parents allocate resources to children,[2] it is perhaps more closely related to the literature that uncovers the parameters of discrete-choice dynamic models using panel data such as Keane and Wolpin (1994), Keane and Moffitt (1998), and Gilleskie (1998). Along with Davis (1998), Gilleskie (1998), and Viscusi and Evans (1990), this paper is one of the few that directly estimates structural parameters of interest to health economists and is the only such paper in the field of mental health. As noted by previous authors (Gilleskie 1998, for example), the structural approach has multiple advantages over other methods of interpreting data such as reduced-form regressions. Specifically, it forces specification of the data generating process to be consistent with utility maximization subject to constraints and it allows policy-makers to forecast changes to behavior and outcomes from changes in policy with no historical precedent. In our view, reduced-form regression techniques are not well-suited for this kind of

[2] See, for example, Becker and Tomes (1976), Lazear and Michael (1988), Rosenzweig and Wolpin (1995 and 1988), and Browning (1992) and Behrman (1997) for two reviews.

forecasting task. The structural approach has an additional benefit in the case of the Fort Bragg Demonstration data in that it facilitates the separate understanding of the influence of each of three different policies (availability of intermediate services, free services, efforts to promote services) bundled together as a social experiment. As far as we know, this is the first paper to directly apply the structural approach using data collected from a social experiment.

This paper also directly contributes to the existing literature on the effectiveness of mental health services for children. Foster (2000) discusses some of the older papers in this literature, many of which suffer from methodological limitations that limit their relevance. More recent papers focus attention on estimates of the marginal impact of an additional dose of services on a child's mental health. Using the Fort Bragg Data, Salzer, Bickman, and Lambert (1999) find no impact of an additional unit of outpatient therapy on child mental health. Bickman et. al. (2002) draw similar conclusions using data from another prominent study in the field, the evaluation of a system of care in Stark County, Ohio. As we discuss later in the paper, these results may be driven by the presence of an unobservable variable that is correlated with both the decision to seek treatment and the observed outcome. Using instrumental variables techniques, Foster (2000) finds there is a sizable correlation between unobserved characteristics and dose. Results in Agnold (2000) support this intuition: Data from a community study in North Carolina show that the conditions of individuals receiving higher doses were deteriorating prior to the period for which dose was defined. As a result, analyses controlling only for level of mental health status underestimated the impact of dose.

Finally, we contribute to the literature analyzing the impact of the Fort Bragg Demonstration on household choices and child outcomes. In many ways, the Fort Bragg experiment represents best practice in the area of children's mental health services and social services more generally.[3] Highlighted in the recent report of the U.S. Surgeon General on mental health (1999), the Demonstration has had enormous impact on the field of children's mental health services. The project severely dampened enthusiasm for the hypothesis that reorganizing service delivery could improve mental health outcomes or could reduce expenditures on mental health services. Further, the project's principal investigator has argued that the Demonstration provides indirect evidence that mental health services are ineffectual (Bickman 1997). Although we agree that the Demonstration did not affect child outcomes, we do estimate that mental health services have a slight but beneficial impact on a child's mental health.

The rest of this paper is organized as follows. In section 2 we specify our model of parental choices and child outcomes. In section 3, we review the data used to estimate this model. Section 4 details the likelihood function and sections 5 and 6 contain analysis, conclusions,

[3]The project received the "Outstanding Evaluation Award" from the American Evaluation Association in 2000.

and public policy implications.

2 Model

At the start of every six month period (periods are denoted by the index t), parents of a Comparison child ($FB = 0$) must decide whether their child will use mental health services, and if so, whether the child will receive outpatient mental health services or both outpatient and inpatient mental health services during the current period. Parents of a child participating in the Fort Bragg Demonstration ($FB = 1$) in period t have these choices as well, but additionally decide whether their child receives non-residential intermediate services and/or residential intermediate services. Parents make these choices for their child in all periods in which their child is younger than 18 years old.

Let the variable i index the available mental health services: $i = 1$ denotes outpatient services, $i = 2$ inpatient services, $i = 3$ intermediate non-residential services, and $i = 4$ intermediate residential services. Correspondingly, let the set of dummy variables d_t^i $(i = 1, \ldots, 4)$ denote parental choices: d_t^1 denotes parents' period t outpatient choice, d_t^2 represents parents' period t inpatient choice, d_t^3 represents parents' period t intermediate non-residential services choice, and d_t^4 denotes parents' period t intermediate residential services choice. Using this notation, Table 1 displays the mental health choice set of parents of Comparison and Demonstration children. Since parents of Comparison children do not have access to intermediate services, their choice set consists of the top three choices of Table 1 (no services, outpatient services only, or outpatient and inpatient services). Parents of children in the Fort Bragg Demonstration have access to all services, so these parents choose from the bottom nine choices of Table 1. Both sets of choices reflect the fact that outpatient services are administered with inpatient and/or intermediate services, a requirement of most mental health service providers.

In every period, parents receive utility from their child's stock of mental health, denoted M_t, and from per-adult-equivalent consumption of market goods measured in thousands of dollars, denoted C_t.[4] Parents also experience random direct utility or disutility from the period t choices themselves. We define parents' period t utility from per-adult-equivalent household consumption, the child's mental health, and mental health choices as

$$\frac{\hat{C}_t^{1-\gamma}}{1-\gamma} + \sum_{i=1}^{4} d_t^i b_t^i, \tag{1}$$

where $\hat{C}_t = \left(\alpha M_t^\beta + (1-\alpha)\, C_t^\beta\right)^{\frac{1}{\beta}}$. $\hat{C}_t$ is the composite good of consumption and child's mental health that provides parents with utility; α measures the importance of mental health relative to consumption in the composite, $\frac{1}{1-\beta}$ is the elasticity of substitution of the

[4]Consumption in specified in thousands of dollars so income has approximately the same scale as our measure of the child's mental health.

two variables in the composite, and γ defines parents' risk-aversion over the composite.

The b_t^i terms capture costs of mental health services for children that are not explicitly included in the model. For example, such costs may include (in units of utility) the time required to drive a child to the mental health clinic, the psychic costs or "stigma" associated with having a child that is using mental health services, etc. These direct utility costs consist of both known deterministic components and random shocks that are realized at the beginning of the period before any decisions are made. For the direct utility for outpatient treatment,

$$b_t^1 = \bar{b}^1 + e_t, \tag{2}$$

with

$$e_t = \rho e_{t-1} + u_t^1, \tag{3}$$

and $0 < \rho < 1$. In (2) and (3), $\bar{b}^1$ is the time-invariant non-random direct utility from using outpatient services, e_t is the auto-regressive random direct utility from outpatient services, and u_t^1 is the random shock to the direct utility of outpatient services.

In contrast to b^1, the other utility shocks b_t^i ($i = 2, 3, 4$) are not auto-regressive but rather consist of a fixed deterministic component and a random shock:

$$b_t^i = \bar{b}^i + u_t^i, \tag{4}$$

for $i = 2, 3, 4$. The random shocks to the marginal utility of services (u_t^i, $i = 1, \ldots, 4$) are jointly drawn from a mean zero Normal distribution with variance-covariance matrix Σ_b. The set of marginal utility shocks are independently drawn over time and in each period are drawn before any of that period's decisions are made. Note that the direct additive utility of any combination of mental health services has an auto-regressive component because outpatient services accompany all other services.

Parents also face a budget constraint that shapes their behavior. We do not observe household assets in our data, so we assume parents do not have savings and cannot borrow against their future income in order to finance either current consumption or their child's use of mental health services. Since parents of Demonstration children do not pay for their child's mental health services, per-adult-equivalent consumption in the household in a given six-month period, C_t, equals one-half the appropriately scaled annual household income (W): $C_t = \left(\frac{1}{AE}\right)\left(\frac{1}{1000}\right)\left(\frac{1}{2}\right)W$ where AE is the number of adult equivalents in the household as defined below. Comparison parents pay a time-invariant CHAMPUS copayment of p^i at the beginning of period t for mental health service i (for $i = 1, 2$), and all remaining income is spent on consumption.[5] For these parents, consumption equals

$$C_t = \left(\frac{1}{AE}\right)\left(\frac{1}{1000}\right)\left[\frac{1}{2}W - \sum_{i-1}^{2} d_t^i p^i\right] \geq 0, \tag{5}$$

where C_t is non-negative because parents cannot borrow. Given the definition of the variable

[5]CHAMPUS has a yearly deductible that we ignore.

FB, per-adult-equivalent consumption in each period for all parents is

$$C_t = \left(\frac{1}{AE}\right)\left(\frac{1}{1000}\right)\left[\frac{1}{2}W - (1 - FB)\sum_{i-1}^{2} d_t^i p^i\right] \geq 0. \tag{6}$$

Because families vary in size, consumption is scaled by the number of adult equivalents in the household (AE) using a formula developed by the Census Bureau (Citro and Michael 1995):

$$AE = (ADLTS + P * KIDS)^F \,, \tag{7}$$

where $ADLTS$ denotes the number of adults in the household and $KIDS$ the number of children (set to the one for these only-child households). Children are therefore counted as P adults and F measures economies of scale in consumption. In estimation, P and F are restricted to lie in the interval $[0, 1]$.[6]

After all of the period t decisions have been made, the child's mental health evolves stochastically. We define M_t as $100 - CBCL_t$, where $CBCL_t$ is the child's reported "Child Behavior Check List" score, a common measure of a child's mental health. The CBCL score has a possible range from 0 (best mental health) to 100 (worst mental health).[7] The child's

[6] $0 \leq P \leq 1$ allows children to consume less than adults and $0 \leq F \leq 1$ allows that household purchases may include public goods. The Census Bureau sets both P and F equal to 0.7.

[7] The CBCL can assume a value higher than 100, but such an occurrence is extremely rare

CBCL score is specified to evolve over time according to the following known stochastic auto-regressive process,

$$
\begin{aligned}
(8) \qquad CBCL_{t+1} &= \theta_{0,t}\,(1-\theta_1) + \theta_1 CBCL_t + \sum_{i=1}^{4} \theta_2^i d_t^i + m_{t+1} \\
\theta_{0,t+1} &= \theta_{0,t} + \sum_{i=1}^{4} \theta_3^i d_t^i .
\end{aligned}
$$

In (8), m_{t+1} is a Normally distributed random shock with mean 0 and variance σ_m^2 that is drawn independently of all other variables in the model and independently over time. m_{t+1} is drawn simultaneously with the period $t+1$ utility shocks and is observed before the period $t+1$ decisions are made. Equation (8) specifies that in the absence of treatment ($d_t^i = 0$ for all i) and with $m_{t+1} = 0$, the child's CBCL will revert to its mean value,[8] $\theta_{0,t}$, which we denote the child's "endowment."

According to (8), mental health services may have no effects, "transitory" effects, "persistent" effects, or both types of effects on a child's mental health. Treatments have transitory effects if they affect a child's CBCL, but not the endowment. The transitory effects of the different treatments are captured by the θ_2^i terms. We define treatment to have persistent effects if the endowment changes, and thus the average value to which the child's CBCL reverts, as a result of treatment. Explaining, if the θ_3^i terms are nonzero, then treatments in the population and not observed in the sample.

[8]This is true for $0 < \theta_1 < 1$, which is imposed in estimation.

administered at period t affect the child's period $t+1$ endowment $\theta_{0,t+1}$, which in turn affect the child's realized CBCL indefinitely into the future. Even though $\theta_{0,t}$ is unobserved to an econometrician, parents are assumed to know $\theta_{0,t}$ in all periods and consider its value when making mental health choices for their child. Thus, the model accounts for treatment selection in a somewhat natural way: Two children with the same observable CBCL score may have different endowments (unobservable to the econometrician) and thus will have fundamentally different mental health outcomes even if the treatment decisions are identical. We would expect that children with the worse endowment, i.e. higher values of $\theta_{0,t}$, to be more likely to seek treatment and indeed our estimates suggest that this is the case.

To finish outlining the model, define X as the vector of time-invariant "state variables" and S_t as the vector of time-varying state variables on which parents base their period t decisions. Given the structure of our model, these vectors are[9]

$$\begin{aligned} X &= \begin{bmatrix} FB & W & ADLTS \end{bmatrix} \\ S_t &= \begin{bmatrix} M_t & \theta_{0,t} & e_{t-1} \end{bmatrix}. \end{aligned} \tag{9}$$

[9]Note that there is a one-to-one mapping of the current period t and the child's age (age_t): We define $t=1$ when the child is born, $t=2$ when the child is six months old, etc. Following convention, the period t shocks to marginal utility are not explicitly included in S_t, even though their values are used to determine the set of optimal decisions.

After all of the shocks to the direct utility from choices have been drawn, parents make choices $d_t^1, \ldots, d_t^4$ in period t to maximize the present value of their expected remaining lifetime utility.

Let the variable j be an index from 1 to 3 (for Comparison parents) or 1 to 9 (for Demonstration parents) for parents' feasible mental health choices, as defined in Table 1. Furthermore, let $d_t^{1,j}, \ldots, d_t^{4,j}$ represent the outpatient, inpatient, and intermediate choices associated with index value j. The expected discounted net present value to parents with state variables X and S_t of choices corresponding to index j, denoted $V_t^j(X, S_t)$, equals

$$V_t^j(X, S_t) = \frac{\hat{C}_t^{1-\gamma}}{1-\gamma} + \sum_{i=1}^{4} d_t^{i,j} b_t^i + \delta E_t \left[V_{t+1}(X, S_{t+1}) \right], \tag{10}$$

$\hat{C}_t = \left(\alpha M_t^\beta + (1-\alpha) C_t^\beta \right)^{\frac{1}{\beta}}$, where $0 < \delta < 1$ is the factor by which parents discount future utility. In any period, parents make the mental health service choices that yield the highest value, implying

$$V_t(X, S_t) = \max_j \left[V_t^j(X, S_t) \right]. \tag{11}$$

When calculating the payoff to their current choices, parents are forward-looking and therefore consider the implications of these choices on their future flow utility: In equation (10), $E_t[V_{t+1}(X, S_{t+1})]$ is parents' period t expected value of $V_{t+1}(X, S_{t+1})$. This expectation integrates parents' future value with respect to their period $t+1$ state variables and utility shocks given their current state variables and choices. We assume that parents understand how preferences and (time-varying) state variables evolve over time, as specified by equations (2) through (8), and use these equations to directly calculate $E_t\left[V_{t+1}\left(X, S_{t+1}\right)\right]$.

Let T be the period when the child is eighteen, i.e. $T = 36$. We assume that once children are eighteen they no longer consume from parents' income, their mental health is permanently fixed at their age 18 level, and their parents no longer make mental health choices. Specifically, when the child is 18 years old, parents receive a "terminal" utility of

$$V_T\left(X, S_T\right) = \left(\frac{1}{1-\delta}\right)\left(\frac{\hat{C}_T^{1-\gamma}}{1-\gamma}\right), \tag{12}$$

where $\hat{C}_T = \left(\alpha M_T^{\beta} + (1-\alpha)\, C_T^{\beta}\right)^{\frac{1}{\beta}}$, $C_T = \left(\frac{1}{\hat{AE}}\right)\left(\frac{1}{1000}\right)\left(\frac{1}{2}\right) W$, and $\hat{AE} = ADLTS^F$. This specification keeps the computation of the model and maximization of the likelihood manageable and does not require estimation of additional parameters.

We do not know how to calculate an analytic solution to the model, which is a function that maps the period, the state space, the utility shocks, and the entire set of parameters of the model to the set of optimal decisions. Instead, we condition on a particular set of parameters and computationally generate a solution to the model at that set of parameters using an algorithm similar to that described by Keane and Wolpin (1994). For an explanation of this algorithm, see the Appendix.

3 Data

Data on demographics, household income, and the mental health of Demonstration and Comparison children were collected every six months for 984 children and adolescents ages 5 through 17 for over two years. These children entered the study between 1990 and 1993, with roughly half entering in 1991, the first full year of the Demonstration. The children were recruited into the study if they had used services prior to the start of the Demonstration, and as a result over ninety percent were using services at the time of their initial interview. Many children stopped using services by the end of the study, so their experiences provide information on children that do not use services. Children who never received mental health services are not included in the data.

For each child in the sample, a care-giver was identified, and that individual was interviewed every six months. In most cases, the care-giver was the child's mother and did not change across interviews. The interviews with the care-giver provide information on the child's mental health, household income, and demographics. We use the Child Behavior Checklist, "CBCL," as our measure of the child's mental health. The CBCL total score is a measure of mental health symptomatology[10] and is commonly used in mental health research.

[10] "Symptomatology" involves counts of behaviors or feelings that serve as signs or indicators of emotional and behavioral problems.

To calculate a child's CBCL score, parents are asked a series of 118 questions about problems their children may be having at home, in school, or with peers during the past 6 months. For each behavior or characteristic, the respondent reports whether the characteristic is never, sometimes, or often true of their child during the previous six months. Responses to these items are summed, and a standardized score is calculated based on national norms for the child's age and gender. The resulting measure has a mean of 50 and a standard deviation of 10 in the population. As mentioned, children with many behavioral problems have high CBCL scores, while children with relatively few behavioral problems have low CBCL scores (Achenbach 1991).

For household income, respondents are asked to place their "total household income in the preceding tax year" in a series of categories: Less than $\$5,000$, between $\$5,000$ and $\$9,999$, between $\$10,000$ and $\$14,999$, between $\$15,000$ and $\$19,999$, between $\$20,000$ and $\$29,000$, between $\$30,000$ and $\$39,000$, between $\$40,000$ and $\$59,000$, and $\$60,000$ or more. We assign household income as the midpoint of the Wave 1 reported category, and households in the highest category are assigned income of $\$75,000$. For demographics, interview data provide information on the child's age, gender, race, household structure (a series of questions that identify individuals living in the household and their relationship to the child), and the education of the child's care-giver. We classify care-givers as being a high school graduate, having some post-secondary education, or having a college degree. The first category includes high school dropouts, but these are few in number because of education requirements for military personnel.

We derive data on mental health service use from two sources. Our primary source of service use data for Comparison children are CHAMPUS transactions. Each CHAMPUS transaction notes the date and mental health service received as well as any payments made by the family. For Demonstration children, all services were either received at or arranged by a central clinic. That clinic maintained a management information system (MIS) that recorded the type of service, the number of service units received, and the date of service. The MIS and CHAMPUS records appear fairly comparable in terms of their completeness and accuracy (Foster, Summerfelt, and Saunders 1996). Both the MIS and the CHAMPUS claims include an identification number for the child's military sponsor and the child's year of birth, and we use this information to link service-use data to specific children in the sample.

We use the MIS and CHAMPUS records to measure service use during the six-month period between interviews. For each period, we identify whether a child received outpatient services (individual therapy, family therapy, group therapy), inpatient services (services administered at a psychiatric hospital, an inpatient ward of a general hospital, or a residential treatment center), intermediate non-residential services (such as in-home services, after-school programs, and latency partial-hospitalization), and/or intermediate residential services (such as services administered in a therapeutic group home). We specify that if a child received outpatient services at least once in the six month period between interviews, that child received "outpatient services" in that period, and we make similar classifications for the other mental health services. Individuals who did not visit an outpatient, inpatient, or intermediate service provider between interviews were assigned as not having received any mental health services.

Interview data were obtained for 984 families, but our analyses are based on a subset of these data. Since we do not observe the CBCL score of siblings and therefore limit ourselves to modeling one-child households, we exclude multiple-child households from our sample. This reduces our sample by 776 observations. We also drop four households from our sample who use inpatient or intermediate services without also using outpatient services, five households with recorded expenditures on mental health services at the Demonstration, and six households where at least one biological or adoptive parent did not live in the household. We drop 20 households that were missing fundamental information (income, child's age, etc.) as of Wave 1 of the study. Finally, we drop 23 households where services data were not available in the core data sources (MIS and CHAMPUS claims). As a result, the sample we use to estimate our model consists of 142 children followed for two and one-half years. Two children in Wave 2, five more in Wave 3, and nine more in Wave 4 are excluded from our sample once they turn 18.

Table 2 describes the initial characteristics of our sample. Consistent with Bickman et. al. (1995), Table 2 does not reveal any significant demographic differences between the Demonstration and Comparison children: The majority of both groups of children are male and white, the care-givers in the study are relatively well educated (which reflects the educational requirements for enlistment in the Army), and the average number of adults in the household is slightly less than 2.[11] The middle portion of Table 2 shows the median, 25th, and 75th percentile of household income and the average CBCL score of the children in our sample. It appears that neither the initial distribution of household income nor the average CBCL score varies between Demonstration and Comparison children. The Wave 1 average CBCL scores show that many of the children in the sample start the study with what appear to be relatively severe mental health problems. To get a better sense of the severity of the problems among these children, it is worth looking at the prevalence of specific CBCL items. In the six months prior to Wave 1, 74% of sample members complained of loneliness, 21% were sometimes or often cruel to animals, 19% had attempted to harm themselves, 14% heard voices, and as mentioned 10% had set fire to property.

The bottom panel of Table 2 shows the mental health service use of children in our

[11]Our measure of adults for Table 2, used to define the variable $ADLTS$ in equation (7), includes parents, step-parents, grandparents, and/or aunts and uncles. A significant percentage of households in our estimation sample include unrelated adults and children over age 18. We do not include these last two groups in our measure of adults.

sample in the first observation period, the period between the first and second interview. As mentioned in the introduction, children were recruited into the study if they recently had used mental health services, and as a result over ninety percent of Demonstration children and eighty percent of the Comparison children use services in the first period. The use of inpatient services is much lower among Demonstration children, and this between-site difference has been attributed to the availability of intermediate services at the Demonstration (Foster, Summerfelt, and Saunders 1996).

Table 3 shows how CBCL scores and mental health service use vary across waves for both Demonstration and Comparison children. Four features of this table deserve mention. First, as shown by the large decrease in average CBCL scores from Wave 1 to Wave 4, the mental health of both Demonstration and Comparison children improved substantially. Figure 1 shows that this improvement was not limited to a narrow fraction of children; the observed distribution of CBCL scores shifted significantly between Wave 1 and Wave 4. Second, as shown in the "Percent Use No Services" row, a higher proportion of Demonstration children use services than Comparison children in all waves of data, but service use for all children dropped precipitously between Wave 1 and Wave 4. Finally, Table 3 indicates that at Wave 4 the difference in CBCL scores for Demonstration and Comparison children is fairly small.

4 Likelihood

The log-likelihood of the data occurring for a household at a given set of parameters can be written as

$$\log\left(\int l\left(E\right)w\left(E\right)dE\right) \tag{13}$$

where E is a vector of random variables, $w\left(E\right)$ is the density of E, and $l\left(E\right)$ is the likelihood for a household at a given draw of E. The object of estimation is the set of parameters that maximize the sum of the log-likehoods for all households.

E is the random vector $\begin{bmatrix} \epsilon_\chi & \epsilon_\iota & u^1_\tau & u^1_{\tau+1} & u^1_{\tau+2} & u^1_{\tau+3} \end{bmatrix}$ and a draw of E identifies the state variables $\theta_{0,t}$ and e_{t-1} for all waves of data. We will show that given any E, we can generate a likelihood, $l\left(E\right)$, which measures how closely the predictions of the model of the mental health choices, CBCL scores, and household expenditures match what is observed in the data. Shown in (13), the likelihood for a household is simply the expected value of $l\left(E\right)$.

Now define E_t as the subset of E that includes only variables dated period t or before, i.e. $E_\tau = \begin{bmatrix} \epsilon_\chi & \epsilon_\iota & u^1_\tau \end{bmatrix}$, $E_{\tau+1} = \begin{bmatrix} \epsilon_\chi & \epsilon_\iota & u^1_\tau & u^1_{\tau+1} \end{bmatrix}$, and so forth. $l\left(E\right)$ can be written as

$$l\left(E\right) = \prod_{t=\tau}^{\tau+3} Pr\left(d^{obs}_t \mid E_t\right) g\left(m_{t+1} \mid E_t\right) h\left(exp_t \mid E_t\right). \tag{14}$$

Later in this section we will explain the terms $Pr\left(d^{obs}_t \mid E_t\right)$, $g\left(m_{t+1} \mid E_t\right)$, and $h\left(exp_t \mid E_t\right)$ but for now note that E_t is defined separately from E to highlight that calculation of these three period t terms does not depend on information dated period $t+1$ or later.

The first two terms of E identify the value of $\theta_{0,\tau}$ and $e_{\tau-1}$ in the first wave of data.[12] $\theta_{0,\tau}$ and $e_{\tau-1}$ are specified to be distributed in the first wave of the sample as[13]

$$\begin{aligned} \theta_{0,\tau} &= \chi_0 + \chi_1 C\hat{B}CL_\tau + \chi_2 a\hat{g}e_\tau + \chi_3 \hat{W} + \chi_4 FB + \chi_5 AD\hat{L}TS + \epsilon_\chi \\ e_{\tau-1} &= \iota_0 + \iota_1 C\hat{B}CL_\tau + \iota_2 a\hat{g}e_\tau + \iota_3 \hat{W} + \iota_4 FB + \iota_5 AD\hat{L}TS + \epsilon_\iota, \end{aligned} \tag{15}$$

with ϵ_χ and ϵ_ι jointly normally distributed with mean 0, variance σ_χ^2 and σ_ι^2 respectively, and covariance $\sigma_{\chi,\iota}$. It is assumed that ϵ_χ and ϵ_ι are uncorrelated with all other shocks in the model. ϵ_χ and ϵ_ι allow for unobserved heterogeneity in child endowments and parent preferences after conditioning on observable Wave 1 state variables.

Once $\theta_{0,\tau}$ and $e_{\tau-1}$ are determined, the sequence of outpatient services utility shocks in E, $\begin{bmatrix} u_\tau^1 & u_{\tau+1}^1 & u_{\tau+2}^1 & u_{\tau+3}^1 \end{bmatrix}$, and sequence of household's observed choices (denoted for period t as $d_t^{obs} = \begin{bmatrix} d_t^{1,obs} & d_t^{2,obs} & d_t^{3,obs} & d_t^{4,obs} \end{bmatrix}$) determine endowments $\theta_{0,\tau}$ and preferences $e_{\tau-1}$ for Waves 2 through 4, periods $t > \tau$. In the case of preferences, $e_t = \rho e_{t-1} + u_t^1$, as specified in equation (3). For the child endowment, $\theta_{0,t+1} = \theta_{0,t} + \sum_{i=1}^{4} \theta_3^i d_t^{i,obs}$, as written in the lower line of equation (8).

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[12] τ is the period (age) of the child in the first wave.

[13] $C\hat{B}CL$, $a\hat{g}e$, $\hat{W}$, and $AD\hat{L}TS$ are the observed Wave 1 values of CBCL, age, income in thousands of dollars, and number of adults residing in the household minus the Wave 1 sample average.

Summarizing all the above, E determines the missing elements of the state space S_t; once the state space is fully specified, the probability that the observed choices occur (and the density of the shocks necessary to produce the observed mental health scores and expenditures on mental health services) can be directly calculated. This is shown in (14), the likelihood for a household at the given draw of E. The first term of (14), the probability that the observed choices occur $Pr\left(d_t^{obs} \mid E_t\right)$, will be explained in the next paragraph. The second term is the density of the CBCL shock, $g\left(m_{t+1} \mid E_t\right)$, required to match the observed CBCL score in period $t+1$ with the CBCL score in t. Rearranging the top line of equation (8), $m_{t+1} = CBCL_{t+1} - \theta_{0,t}\left(1-\theta_1\right) - \theta_1 CBCL_t - \sum_{i=1}^{4} \theta_2^i d_t^{i,obs}$.[14] The third term is the density of reported expenditures of Comparison parents when expenditures are observed, $h\left(exp_t \mid E_t\right)$, given predicted expenditures for these parents equal $\sum_{i=1}^{2} p_t^i d_t^{i,obs}$.[15]

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[14]Note that m_{t+1} is not observed in the fourth data period; this requires a 5th Wave of CBCL data. Related, there are a substantial number of households for which the CBCL score is not observed in Waves 2, 3, or 4. In all these cases, we set $g\left(.\right) = 1$ in (14). If the CBCL score in Waves 2, 3, or 4 is not observed, we draw m_{t+1} from $g\left(.\right)$ and include this draw of m_{t+1} in E. Given this draw, we use equation (8) to generate a CBCL value for period $t+1$ which becomes part of the vector S_{t+1}.

[15]The model specifies that all Comparison households pay the same price for each mental health service. In the data, out of pocket expenses vary holding the provided mental health

Returning to $Pr\left(d_t^{obs} \mid E_t\right)$, the model predicts a probability of the observed mental health choices in period t, conditional on E_t, because the inpatient and intermediate services utility shocks u_t^2, u_t^3, and u_t^4 are not included in E_t. This probability is expressed as the expected value of an indicator function,

$$\text{(16)} \quad Pr\left(d_t^{obs} \mid E_t\right) = \int I\left[d_t^{obs} = d_t^*\left(X, S_t, u_t \mid E_t\right)\right] f\left(u_t^2, u_t^3, u_t^4 \mid E_t\right) d\left(u_t^2, u_t^3, u_t^4\right).$$

This indicator function $I\left[d_t^{obs} = d_t^*\left(X, S_t, u_t \mid E_t\right)\right]$ equals 1 if the observed choice is the same as the model's predicted optimal choice for the household in that period, denoted $d_t^*(.)$.[16] The model's predicted optimal choice depends on the time-invariant state variables $X = \left[\begin{array}{ccc} FB & W & ADLTS \end{array}\right]$, time-varying state variables $S_t = \left[\begin{array}{ccc} M_t & \theta_{0,t} & e_{t-1} \end{array}\right]$, and utility shocks $u_t = \left[\begin{array}{cccc} u_t^1 & u_t^2 & u_t^3 & u_t^4 \end{array}\right]$. Referring to specific arguments of d_t^* in (16), $u_t^1 \in E_t$, and, S_t is consistent with E_t, M_t, and the sequence of observed choices up to $t-1$. The expectation in (16) is taken with respect to the values of the utility shocks u_t^2, u_t^3, and u_t^4; the density of u_t^2, u_t^3, and u_t^4, $f\left(u_t^2, u_t^3, u_t^4 \mid E_t\right)$, is conditional on the specific draw of $u_t^1 \in E_t$.[17]

Applying Monte-Carlo integration directly to (13), (14), and (16) yields the consistent

service fixed. To estimate prices most applicable to the model, the difference of the natural log of reported expenditures of Comparison households and the natural log of the model's predicted expenditures is specified as a random variable with mean 0 and variance σ_p^2.

[16]See the Appendix for details on the computation of d_t^*.

[17]If we index the row and column elements of the variance-covariance matrix Σ_b

estimator[18]

(17)

$$\log\left(\frac{1}{N_1}\sum_{E}\prod_{t=\tau}^{\tau+3}\left[\frac{1}{N_2}\sum_{\left(u_t^2,u_t^3,u_t^4\right)} I\left[d_t^{obs}=d_t^*\left(X,S_t,u_t,\mid E_t\right)\right]\right]g\left(m_{t+1}\mid E_t\right)h\left(exp_t\mid E_t\right)\right)$$

where N_1 is the number of draws of E from its unconditional distribution and N_2 is the number of draws of $(u_t^2,\ u_t^3,\ u_t^4)$ from its conditional distribution (conditioning on $u_t^1 \in E_t$).[19] (17) is not smooth in the parameters of the model for reasonable values of N_1 and N_2.[20] We desire smoothness in order to compute standard errors, and so we re-

as $\Sigma_b\left(a,b\right)$, then $\left(u_t^2,u_t^3,u_t^4\right)$ conditional on u_t^1 is Normally distributed with mean $u_t^1\left[\Sigma_b\left(2:4,1\right)/\Sigma_b\left(1,1\right)\right]$ and variance $\Sigma_b\left(2:4,2:4\right)-\left[\Sigma_b\left(2:4,1\right)\Sigma_b\left(1,2:4\right)/\Sigma_b\left(1,1\right)\right]$.

[18]We should note that this likelihood and our estimator can be viewed as an application of the GHK algorithm. See Keane (1994) for details.

[19]When the observed choice is $j=1$ (no services) or $j=2$ (outpatient services only) we analytically determine a restricted region from which to draw u_t^1 in E and adjust the likelihood appropriately. For the case $j=1$, we find the set of u_t^1 for which $j=1$ is strictly preferred to $j=2$; for $j=2$, we find the u_t^1 where $j=2$ is strictly preferred. This region can be defined analytically due to the fact that the period $t+1$ expected value functions are approximated via quadratic functions of the state space: See the Appendix for details on the model solution.

[20]We set $N_1=100$ and $N_2=50$.

place $I\left[d_t^{obs} = d_t^*\left(X, S_t, u_t, \mid E_t\right)\right]$ with $\hat{I}\left[d_t^{obs} = d_t^*\left(X, S_t, u_t, \mid E_t\right)\right]$, a consistent approximation that is a smooth function of the model parameters. Similar to Eckstein and Wolpin (1999), this smoothed indicator function is set equal to

$$\hat{I}\left[d_t^{obs} = d_t^*\left(X, S_t, u_t, \mid E_t\right)\right] = \frac{\exp\left(\frac{V_t^{obs} - V_t^*}{\lambda}\right)}{\sum_j \exp\left(\frac{V_t^j - V_t^*}{\lambda}\right)} \tag{18}$$

where (a) V_t^{obs} is the value to parents of observed choices d_t^{obs} given time-invariant state variables X, time-varying state variables S_t, and the vector of utility shocks u_t (the latter two variables appropriately conditioned on the draw E_t); (b) V_t^* is the value to parents of optimal choices, where optimal choices are given by $d_t^*\left(X, S_t, u_t \mid E_t\right)$; (c) V_t^j is the value to parents of arbitrary choice j given X, S_t, u_t, and conditional on E_t; and (d) λ is a smoothing parameter. The summation in the denominator is over all feasible choices, including the observed choices, where feasible choices are indexed by j as in Table 1.[21]

After making this substitution, we find the parameters that maximize

(19)

$$\sum \log\left(\frac{1}{N_1}\sum_E \prod_{t=\tau}^{\tau+3}\left[\frac{1}{N_2}\sum_{\left(u_t^2, u_t^3, u_t^4\right)} \hat{I}\left[d_t^{obs} = d_t^*\left(X, S_t, u_t, \mid E_t\right)\right]\right] g\left(m_{t+1} \mid E_t\right) h\left(exp_t \mid E_t\right)\right),$$

where the outer summation is over all households in the sample.

[21] Consistency of this estimator requires that λ approach 0 as the sample size gets large. We set $\lambda = 0.05$ in estimation.

5 Analysis

The maximized value of the log-likelihood is $-1,648.86$. Table 4 shows estimates of all model parameters and approximate standard errors, generated as the outer product of the estimated scores. Very few parameters are precisely independently estimated, while some parameters, specifically P and F, appear not well identified.

Taking the point estimates of Table 4 as unbiased, five results emerge from the estimates for this sample of households. First, the unconditional expectation of average additive utility of mental health services is negative ($\bar{b}^i$ is less than zero for $i = 1, \ldots, 4$). As long as e_{t-1} is not too large then on average parents dislike services; mental health services must improve a child's mental health for parents to consistently choose to use them. Second, mental health services have modest but beneficial persistent effects on a child's mental health (θ_3^i are less than zero for $i = 1, \ldots, 4$). These effects may be hard to observe for any one child because the random shock to the CBCL can be is quite large: The standard deviation of the shock to the CBCL ($\sqrt{\sigma_m^2}$) is almost 9 CBCL points. Third, inferred from the estimate $\chi_0 = 48.63$, the average child in the sample had an essentially normal endowment of mental health at Wave 1. Interestingly, the standard deviation of the unobserved component of the endowment ($\sqrt{\sigma_\chi^2}$) is only 6.12 CBCL points, suggesting most children in the study had a relatively healthy endowment of mental health as of Wave 1 (the population standard deviation of the CBCL is 10 points). Fourth, reflective of the selection of the sample, parents on average entered

Wave 1 with a high value of e_{t-1} ($\iota_0 = 6.34$), explaining the high use of services in the Wave 1. Abstracting from subsequent values of u_t^1, the initial value of e_{t-1} decayed at 20 percent per period ($\rho = 0.80$), helping to explain the decline in the use of services across Waves. Finally, efforts to promote the use of services at the Demonstration were largely successful, indicated by the estimated value of $\iota_4 = 1.10$: All else equal, parents at the Demonstration experienced less disutility from using services than Comparison parents.

A simulation of the model at the estimated parameters shows the model nicely matches many salient features of the data.[22] Table 5 details the model's baseline predicted choice distribution, by Wave, for Demonstration and Comparison parents in the estimation sample. Unless otherwise noted, this simulation is referred to as the "Baseline" simulation because the decisions and evolution of state variables of households are generated using the same economic environment as that used to estimate the model parameters. As shown in Table 5, the model replicates both the overall decline in the use of services over time as well as the distribution of mental health choices at all points in time. Figure 2 plots the model's predicted distribution of CBCL scores in Wave 4 for households that report a Wave 4 CBCL score. As is evident, the model very closely matches the entire distribution of Wave 4 CBCL scores.[23]

[22]See the Appendix for a description of how a simulation is performed.

[23]The model does not do quite as good a job fitting the reported distribution of CBCL

Three sets of counterfactual simulations of the model are performed to analyze policy questions relevant to the field of childrens' mental health. In each counterfactual simulation the values of all endowment, utility, and mental health shocks remain unchanged from the Baseline simulation, but the economic environment of the households in the estimation sample is altered and the optimal mental health choices and resulting child outcomes are calculated. The remainder of this section provides detailed analysis of each counterfactual simulation. Note that the conclusions drawn from these simulations many not apply to the entire population because of sample selection issues and the unique nature of the data.

5.1 Impact of Mental Health Services on CBCL Scores

To understand the impact of observed parent choices on the CBCL scores of children, a counterfactual simulation is performed in which parents never enroll their child in mental health services. Comparisons of the counterfactual distribution of Wave 4 CBCL scores (dashed line, Figure 3) with the simulated baseline Wave 4 CBCL scores (dotted line) reveal the extent to which we estimate parents' mental health choices improved their child's Wave 4 mental health. Seen from the dashed line, the median child in the estimation sample

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scores in Waves 2 and 3 (not shown). Although most of the predicted distribution closely matches the data, the predicted CBCL for the 40th, 50th, and 60th centiles are approximately 2 CBCL points too high in both waves.

had a normal endowment of mental health as of Wave 1; the median value of the Wave 4 CBCL in the counterfactual simulation is 52, close to the median value of the Wave 1 endowment, 49. Much of the improvement in child CBCL scores from Wave 1 to Wave 4 is therefore due to reversion to the mean. Comparing the dashed line to the dotted line, it appears parents' choices of mental health services at best modestly improved the Wave 4 distribution of CBCL scores: At most points along the distribution, the improvement in the CBCL score (the distance between the dashed and dotted lines) is 1 CBCL point.

Of course, the model allows for parents to choose a larger improvement: In any each period Comparison parents can improve their child's mental health endowment by about 1 CBCL point and Demonstration parents by nearly 3 CBCL points by choosing all available mental health services. However, in the baseline simulations the majority of parents choose to enroll their child only in outpatient services and these services taken alone have a relatively small impact on the child's endowment of mental health ($\theta_3^1 = -0.56$). Further, the majority of service use occurs in Waves 1 and 2. Since the CBCL quickly reverts to its endowment ($\theta_1 = 0.56$), outpatient services chosen in Waves 1 and 2 have little impact on Wave 4 CBCL scores.

5.2 Impact of Demonstration on Choices and Outcomes

As we have documented, the Fort Bragg Demonstration provided a unique environment for parents to make mental health choices for their children: Intermediate services not easily accessible elsewhere were made available, all services were freely provided, and efforts were made to promote the use of mental health services. To understand the marginal impact of each aspect of the Demonstration on parental choices and child outcomes, three counterfactual experiments are performed. In the first experiment, "No Intermediate Services," Demonstration parents are specified to no longer have access to intermediate services, but the environment of the Demonstration is otherwise unchanged. In the second experiment, "Costly Services," Demonstration parents face the restricted choice set of the No Intermediate Services experiment but must also pay the same price for inpatient and outpatient services as Comparison parents. The final experiment, "No Promotion," is identical to the Costly Services experiment in all regards except ι_4 of equation (15) is set equal to zero: By setting ι_4 to zero in the No Promotion experiment, the impact of the promotion of mental health services on the choices and outcomes of Demonstration households is identified.

Table 6 shows the simulation results from the Baseline simulation (the unchanged environment of the Demonstration) and the three counterfactual experiments mentioned above. For each wave in each simulation, this table shows the full set of mutually exclusive choice probabilities.[24] From comparisons of the No Intermediate Services experiment with the Baseline, it is clear that the intermediate services offered by the Demonstration substantially changed the mental health choices of households. Many parents who would have chosen intermediate services for their child in the baseline (lines 13 and 14) instead enroll their child in inpatient services (line 10). The other choices changed little in comparison. In total, these changes do not affect the Wave 4 simulated distribution of child CBCL scores (not shown).

The marginal impact of the availability of free services at the Demonstration on parent choices can be inferred by comparing the simulated choice distribution of the Costly Services with the No Intermediate Services counterfactual experiments. As is evident from Table 6, the price-elasticity with respect to all choices in this sample is zero: Parents simply do not change their choices in response to a change in the price of services.[25] Based on the parameter estimates in Table 4, it is clear that household utility increases with consumption all else held constant. It appears, however, that the variation in utility due to random changes in the direct marginal utility of choices is a more important determinant of mental health service use than the variation in utility from reasonable changes to household consumption.

[24]To simplify the layout of this table, non-residential and residential intermediate services are grouped together.

[25]Other simulations (not shown) show that parents in this sample are income-inelastic as well.

Finally, comparisons of the No Promotion to Costly Services simulation reveal that efforts to promote the use of services at the Demonstration affected parents' use of outpatient services (lines 7 and 8) but had much less of an impact on the use of inpatient services (lines 11 and 12). The reduction in the use of services in the No Promotions counterfactual simulation increases Wave 4 CBCL scores by about 0.1 points across the entire distribution of CBCL scores when compared to the Costly Services simulation (not shown).

Although they are not shown, the Costly Services, No Intermediate Services, and Baseline Wave 4 CBCL distributions are all nearly identical. At all points of the Wave 4 distribution of CBCL scores, the impact of all aspects of the Demonstration is at most 0.5 CBCL points. We conclude that the Demonstration altered parents' choices but did not affect child outcomes.

5.3 Elimination of Inpatient Services

In the last counterfactual experiment, inpatient services are made unavailable to any household but non-residential and residential intermediate services are available to all households,[26] each with marginal cost of $281, the estimated price of inpatient services. This experiment allows us to determine whether the parameter estimates support the commonly held view among service providers and child advocacy groups that inpatient care is over-utilized. This experiment also highlights the benefits of structural estimation: This particular policy

[26]Referring to Table 1, parents can choose j equal to 1, 2, 4, 6, or 8.

experiment has no historical empirical analogue with which reduced-form techniques may be applied to analyze the potential impact of the policy change.

The base case for Comparison parents in this experiment is specified to be the Baseline simulation of the model as reported in Table 5. However, the base case for Demonstration households is the "No Promotion" experiment from Table 6, the scenario where Demonstration parents do not have access to intermediate services, outpatient and inpatient services are costly, and no efforts were made at the Demonstration to promote service use. By setting the base case to the No Promotion scenario for Demonstration children, we can directly measure the impact of this counterfactual policy on the outcomes of Demonstration children had the Demonstration never happened. Table 7 shows the choice distribution of households in all Waves. Relative to baseline, parents choose to use more outpatient services in all Waves, while the use of more intensive treatments remains constant in the early part of the sample and then declines modestly in Waves 3 and 4.[27] As a result of the increased use of services, the CBCL scores of the bottom 30% of the distribution (the highest 30% of CBCL scores) improved by about 0.5 CBCL points in the counterfactual experiment (not shown). For perspective, this is about the same impact the Demonstration had on CBCL scores. We would conclude from this experiment that inpatient services can be replaced with intermediate services without any adverse consequences to child outcomes, at least among

[27]This result is apparent by comparing row $j = 3$ to $j = 4 + 6 + 8$.

this sample of single-child households.

6 Conclusions and Policy Implications

In this paper, we specify a model where parents care about household consumption, their child's mental health, and the disutility of mental health services. We estimate the structural parameters of the model using a procedure that accounts for missing data, sample selection, and unobserved heterogeneity in child endowments and parental preferences. Estimates of this model suggest that mental health services have slight but beneficial effects on a child's mental health that may be hard to observe because the variance of the shock to mental health scores is quite large. The average disutility associated with these services, however, limits their use. Estimates also show that the children entered the study with an essentially normal endowment of mental health but parents entered the study with an atypically small disutility from using services, explaining the high use of services in early waves. Counterfactual simulations of the model show that mental health services explain a modest (at best) fraction of the improvement of the mental health of children in the estimation sample, that the Demonstration influenced mental health choices but not child outcomes, and the increased use of services of Demonstration households relative to Comparison households is attributable almost entirely to efforts to promote the use of services at the Demonstration.

The final policy simulation shows that inpatient services can be eliminated and replaced with costly intermediate services in the choice set of parents and child outcomes would not suffer any adverse consequences.

The parameter estimates and counterfactual simulations of the previous section address three larger themes surrounding the provision of mental health services: The effect of mental health services on a child's mental health, the role of "parity" in the use of mental health services, and the importance of "stigma."

Although our analyses show that the benefits of mental health services may be small, previous studies may have underestimated the impact of mental health services on a child's mental health. First, the impact of services may be hard to observe due to the inherent variability of the CBCL score itself. More importantly, many previous studies fail to account for two phenomena that are explicitly addressed in this paper, namely, that the child's CBCL endowment is unobservable and correlated with the decision to seek treatment, and, that the endowment may itself be affected by treatment. Simulations of the model show that, conditional on the child's observed CBCL and other state variables, the probability that parents enroll their child in mental health services increases for children with worse mental health endowments, i.e. higher values of $\theta_{0,t}$. Studies that compare outcomes of observably similar children who were not randomly assigned to treatment will therefore underestimate the effects of mental health services: Without treatment, children that used mental health services would have had higher CBCL scores at the end of the study than children who did not use services.

A second major theme in research on mental health services is the importance of parity, defined as the provision of mental health services under the same financial terms as general medical services. Both researchers and politicians have been preoccupied with the actual and anticipated impact of parity laws. A recent issue of a leading journal in the health services field, *Health Affairs*, reviewed the state of mental health research, and parity was a major focus. (See, for example, Burnam and Escarce 1999 and Mechanic and McAlpine 1999). Legislative activity has focused on parity as well. The Mental Health Parity Act was passed in 1996, and several states have passed their own laws to further strengthen parity requirements.

Our results suggest that for this sample of households, the emphasis on parity may not be that important because the use of mental health services is not sensitive to prices. Of course, this result may not be widely applicable: We study single-child households and our data do not include children who have never used services. Nonetheless, our result conflicts with earlier findings, including those of the Rand Health Insurance Experiment (HIE). Research from the HIE suggests that children's use of medical services is especially sensitive to the financial terms under which care is provided.[28] We believe an important area of future

[28]In the HIE, when parents paid no costs, per-child expenditures were 10% greater than

research reconciles our result with that of the HIE.

Finally, the role of stigma in the provision of mental health services was a major focus of the Surgeon General's recent report on mental health (Office of the U.S. Surgeon General 1999). The report's bottom line was that mental illness is substantially under-treated. While the report offers several explanations, the role of stigma is highlighted. Consistent with that explanation, we find that the direct additive disutility of services limits the extent to which parents enroll their children in mental health services.

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when families covered 25% of the costs of care (Leibowitz et. al. 1985). This result is generally consistent with a small body of research on cost-sharing and the use of mental health services by children and adolescents (Tsai et. al. 1988, Patrick et. al. 1993).

Appendix

A Solution Algorithm

As noted in the model section, in any period of the model the time-varying vector of state variables consists of three elements, $S_t = \begin{bmatrix} M_t & \theta_{0,t} & e_{t-1} \end{bmatrix}$. For purposes of solving the model, we replace M_t in S_t with $\hat{M}_t$, which is the value of the child's mental health after all period $t-1$ decisions have been made but before the mental health shock m_t has been drawn: Referring to equation (8), $M_t = \hat{M}_t + m_t$. By definition, $\hat{M}_t$ and $\theta_{0,t}$ are bounded between 0 and 100. Although e_{t-1} is not necessarily bounded, we restrict e_{t-1} to lie in a closed interval; during simulations of the model, we check that the simulated value of e_{t-1} never achieves its upper or lower bound. We use a recursive solution algorithm to solve the model at a given set of parameters. We repeat the following procedure for all possible combinations of the $X = \begin{bmatrix} FB & W & ADLTS \end{bmatrix}$ vector: For $FB = 1$ (Demonstration) and $FB = 0$ (Comparison), eight different possible values of household income W,[29] and $ADLTS = 1, 2, 3$.

To start the backwards recursion, we randomly draw K sets of $\hat{M}_T$, $\theta_{0,T}$, and e_{T-1} from the closed intervals containing their feasible values. This draw gives us $k = 1, \ldots, K$ sets

[29] For the exact eight income values we use, refer to the data section of the paper.

of period T state variables, S_T^k for $k = 1, \ldots, K$. Given a particular draw of S_T^k, we draw L sets of the mental health shock m_T^l, indexed by $l = 1, \ldots, L$. For each draw of m_T^l, we compute the child's terminal mental health score $M_T^{k,l} = \hat{M}_T^k + m_T^l$, and then compute the terminal value to parents at $M_T^{k,l}$, $\theta_{0,T}$, and e_{T-1}, denoted $V_T\left(S_T^k, m_T^l\right)$, as defined by equation (12). $E_{T-1}\left[V_T\left(S_T^k\right)\right]$ is computed as the average value of $V_T\left(S_T^k, m_T^l\right)$, i.e. $E_{T-1}\left[V_T\left(S_T^k\right)\right] = \frac{1}{L}\sum_{l=1}^{L} V_T\left(S_T^k, m_T^l\right)$. We repeat this for all K vectors of S_T^k. Similar to Keane and Wolpin (1994), we regress the resulting set of K expected values on a quadratic function of the K vectors of S_T^K. This regression yields a predicted value of $E_{T-1}\left[V_T\left(S_T\right)\right]$ for any S_T, not just at the S_T^k that were directly computed. We assume that any value of $E_{T-1}\left[V_T\left(S_T\right)\right]$ predicted by this regression is correct.

At this point, we move back one period to $T-1$ and draw K sets of $\hat{M}_{T-1}$, $\theta_{0,T-1}$, and e_{T-2} to yield K sets of the state vector, S_{T-1}^k for $k = 1, \ldots, K$. For each draw of S_{T-1}^k, we draw L sets of the mental health shock m_{T-1}^l and utility shocks $u_{T-1}^1, \ldots, u_{T-1}^4$ from the appropriate distribution. Denote a particular draw of these shocks as $m_{T-1}^l, u_{T-1}^{1,l}, \ldots, u_{T-1}^{4,l}$. Given the draw of the state vector S_{T-1}^k and draw of the shocks $m_{T-1}^l, u_{T-1}^{1,l}, \ldots, u_{T-1}^{4,l}$, we need to know the value of the expectation in equation (10) to calculate the payoff for arbitrary choice j, $d_{T-1}^{1,j}, \ldots, d_{T-1}^{4,j}$. Omitting the time-invariant vector X to reduce notation, this expectation can be written as

$$E_{T-1}\left[V_T\left(S_T\right) \mid S_{T-1}^k, d_{T-1}^{1,j}, \ldots, d_{T-1}^{4,j}, m_{T-1}^l, u_{T-1}^{1,l}\right]. \tag{20}$$

Given S^k_{T-1}, $d^{1,j}_{T-1},\ldots,d^{4,j}_{T-1}$, m^j_{T-1}, and $u^{1,l}_{T-1}$, $\theta_{0,T}$ is completely determined from the 2nd row of equation (8), e_{T-1} is completely determined from (3), and by the top row of equation (8), $\hat{M}_T$ is determined from M_{T-1} and $d^{1,j}_{T-1},\ldots,d^{4,j}_{T-1}$. This implies that all elements of S_T are known and $E_{T-1}\left[V_T\left(S_T\right)\right]$ can be calculated for any S_T using the quadratic approximation discussed in the previous paragraph. Once the expectation in (20) has been calculated, at the particular draw of the state space and utility shocks, we find the maximizing choice of $d^{1,j}_{T-1},\ldots,d^{4,j}_{T-1}$, determined by equation (11), by repeating these steps for $j=1,\ldots,3$ (Comparison parents) or $j=1,\ldots,9$ (Demonstration parents).

Denote the value of the optimal choice given S^k_{T-1} at this given draw of $m_{T-1},u^{1,l}_{T-1},\ldots,u^{4,l}_{T-1}$ as $V_{T-1}\left(S^k_{T-1}\mid m^l_{T-1},u^{1,l}_{T-1},\ldots,u^{4,l}_{T-1}\right)$. Now define $E_{T-2}\left[V_{T-1}\left(S^k_{T-1}\right)\right]$ as the expected value of having state space S^k_{T-1} in period $T-1$ prior to the mental health and utility shocks being drawn. We set $E_{T-2}\left[V_{T-1}\left(S^k_{T-1}\right)\right]$ equal to the average value of $V_{T-1}\left(S^k_{T-1}\mid m^l_{T-1},u^{1,l}_{T-1},\ldots,u^{4,l}_{T-1}\right)$ over the L draws of the mental health and utility shocks. We calculate $E_{T-2}\left[V_{T-1}\left(S^k_{T-1}\right)\right]$ for all K draws of the state vector S^k_{T-1} and, as in period T, regress this set of expected values on a quadratic function of the K values of S^k_{T-1}. As before, this regression yields predicted values of $E_{T-2}\left[V_{T-1}\left(S_{T-1}\right)\right]$ at all possible S_{T-1}; we assume these predicted values are always correct.

At this point, the process as just described repeats for $T-2$, then $T-3$, etc. all the way back to the first decision period. In every period, $K=100$ and $L=50$.

B Simulation Procedure

A simulation is accomplished by repeating the following process 100 times for each household in the estimation sample. First, each household's time-invariant state variables (income, number of adults, Demonstration status) and the Wave 1 CBCL score are copied directly from the data. Next, ϵ_χ and ϵ_ι are drawn and $\theta_{0,\tau}$ and $e_{\tau-1}$ are determined for the first simulation period ($t = \tau$) according to equation (15).[30] Then, the utility shocks $u_t^1, \ldots, u_t^4$ are drawn and the household's optimal choices for the first simulation period are calculated. At this point, e_τ is updated according to equation (3), $m_{\tau+1}$ is drawn, and, using the simulated choices, $\theta_{0,\tau+1}$ and $M_{\tau+1}$ are updated according to equation (8). The process as just described (determination of the household's optimal choices and subsequent evolution of state variables) repeats for periods $\tau + 1$ through $\tau + 3$.

[30]The first simulation period is the same as the first estimation period.

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TABLE 1

PARENTS' SET OF MENTAL HEALTH CHOICES

Choice Set	Index j	d_t^1	d_t^2	d_t^3	d_t^4	Outpatient	Inpatient	Intermediate Non-Residential	Intermediate Residential
	1	0	0	0	0	No	No	No	No
$FB = 0$	2	1	0	0	0	Yes	No	No	No
	3	1	1	0	0	Yes	Yes	No	No
	1	0	0	0	0	No	No	No	No
	2	1	0	0	0	Yes	No	No	No
	3	1	1	0	0	Yes	Yes	No	No
	4	1	0	1	0	Yes	No	Yes	No
$FB = 1$	5	1	1	1	0	Yes	Yes	Yes	No
	6	1	0	0	1	Yes	No	No	Yes
	7	1	1	0	1	Yes	Yes	No	Yes
	8	1	0	1	1	Yes	No	Yes	Yes
	9	1	1	1	1	Yes	Yes	Yes	Yes

TABLE 2

CHARACTERISTICS OF INITIAL WAVE OF DATA

Wave 1 Characteristic		Full Sample 142 children	Demonstration 89 children	Comparison 53 children
Percent White		70.4	67.4	75.4
Percent Male		61.3	57.3	67.9
Caretaker: Some College[1]		85.2	91.0	75.5
Caretaker: College Grad		26.8	31.5	18.9
Adults in HH		1.8	1.7	1.9
Income: Median		$25,000	$25,000	$25,000
Income: 25th Percentile		$17,500	$25,000	$17,500
Income: 75th Percentile		$35,000	$35,000	$35,000
Child CBCL: Mean (Standard Deviation)		63.5 (9.5)	63.0 (9.4)	64.3 (9.7)
Percent Using Services:	Outpatient	90.8	96.6	81.1
	Inpatient	20.4	12.4	34.0
	Intermediate Non-Residential	9.9	15.7	0.0
	Intermediate Residential	7.8	12.4	0.0

1. Refers to the percentage of households where the primary care-giver has had some college education.

TABLE 3

CBCL AND MENTAL HEALTH SERVICE USE BY SITE AND WAVE[1,2]

Variable	Site	Wave 1	Wave 4
Average CBCL	Demonstration	63.0	50.4
	Comparison	64.3	53.6
Percent Use No Services	Demonstration	3.4	70.9
	Comparison	18.9	84.4
Percent Use Outpatient	Demonstration	96.6	29.1
	Comparison	81.1	15.6
Percent Use Inpatient	Demonstration	12.4	1.3
	Comparison	34.0	2.2
Percent Use Intermediate Non-Residential	Demonstration	15.7	2.5
	Comparison	0.0	0.0
Percent Use Intermediate Residential	Demonstration	12.4	2.5
	Comparison	0.0	0.0

1. We observe CBCL scores and service use for 89 Demonstration children and 53 comparison children in Wave 1. In Wave 4, we have service use data for 79 Demonstration children and 45 Comparison children and observe Wave 4 CBCL scores for 44 Demonstration children and 29 Comparison children.

2. The CBCL score in the Wave x column refers to the child's CBCL at the Wave x interview. The percent that use services in the Wave x column refers to the percent of children that use services between Wave x and Wave x+1.

TABLE 4

MODEL PARAMETER ESTIMATES AND STANDARD ERRORS

PREFERENCE PARAMETERS

	Variable	Estimate	SE
α	relative preference for mental health	0.93	0.48
β	elasticity of substitution parameter	-0.63	1.00
γ	coefficient of risk aversion	1.46	0.16
δ	discount factor	0.99	0.00
	Adult Equivalence Scale		
P	coefficient on kids	0.84	56.22
F	exponent	0.95	5.35
	Marginal Utility of Choices:		
$\bar{b}^1$	outpatient	-4.87	2.57
$\bar{b}^2$	inpatient	-1.02	1.80
$\bar{b}^3$	intermediate non-residential	-1.50	1.85
$\bar{b}^4$	intermediate residential	-1.87	1.85
ρ	persistence parameter	0.80	0.08

TABLE 4

MODEL PARAMETER ESTIMATES AND STANDARD ERRORS (CONTD.)

UTILITY SHOCK VARIANCE-COVARIANCE MATRIX PARAMETERS

	Variable	Estimate	SE
	Variances		
$\Sigma_b(1,1)$	outpatient shock	0.93	0.75
$\Sigma_b(2,2)$	inpatient shock	0.10	0.39
$\Sigma_b(3,3)$	int. non-residential shock	0.04	0.18
$\Sigma_b(4,4)$	int. residential shock	0.03	0.21
	Correlations		
$\frac{\Sigma_b(1,2)}{\sqrt{\Sigma_b(1,1)\Sigma_b(2,2)}}$	outpatient, inpatient shock	0.01	0.40
$\frac{\Sigma_b(1,3)}{\sqrt{\Sigma_b(1,1)\Sigma_b(3,3)}}$	outpatient, int. non-residential shock	-0.03	0.78
$\frac{\Sigma_b(1,4)}{\sqrt{\Sigma_b(1,1)\Sigma_b(4,4)}}$	outpatient, int. residential shock	0.85	2.77
$\frac{\Sigma_b(2,3)}{\sqrt{\Sigma_b(2,2)\Sigma_b(3,3)}}$	inpatient, int. non-residential shock	-0.25	1.59
$\frac{\Sigma_b(2,4)}{\sqrt{\Sigma_b(2,2)\Sigma_b(4,4)}}$	inpatient, int. residential shock	0.11	1.18
$\frac{\Sigma_b(3,4)}{\sqrt{\Sigma_b(3,3)\Sigma_b(4,4)}}$	int. non-res, int. residential shock	-0.55	0.83

TABLE 4

MODEL PARAMETER ESTIMATES AND STANDARD ERRORS (CONTD.)

CBCL AND PRICE PARAMETERS

	Variable	Estimate	SE
θ_1	lag CBCL	0.56	0.07
	Transitory Effects of Services:		
θ_2^1	outpatient	-0.26	0.42
θ_2^2	inpatient	0.01	0.31
θ_2^3	intermediate non-residential	-0.08	0.52
θ_2^4	intermediate residential	-0.21	0.48
	Persistent Effects of Services		
θ_3^1	outpatient	-0.56	0.37
θ_3^2	inpatient	-0.48	0.85
θ_3^3	intermediate non-residential	-0.84	0.78
θ_3^4	intermediate residential	-0.96	1.12
σ_m^2	variance of CBCL shock	79.48	7.84
p_1	price of outpatient services	98.02	32.45
p_2	price of inpatient services	280.91	117.82
σ_p^2	variance of (log) reported prices	2.41	0.40

TABLE 4

MODEL PARAMETER ESTIMATES AND STANDARD ERRORS (CONTD.)

HETEROGENEITY IN ENDOWMENTS AND PREFERENCES PARAMETERS

	Variable	Estimate	SE
	correlates of $\theta_{0,\tau}$		
χ_0	constant	48.63	3.22
χ_1	$\hat{CBCL}_\tau$	0.34	0.15
χ_2	$\hat{age}_\tau$	-0.11	0.30
χ_3	$\hat{W}$	-0.11	0.09
χ_4	FB	0.47	1.59
χ_5	$AD\hat{L}TS$	-0.19	1.35
σ_χ^2	variance of ϵ_χ	37.50	26.02
	correlates of $e_{\tau-1}$		
ι_0	constant	6.34	2.75
ι_1	$\hat{CBCL}_\tau$	-0.01	0.02
ι_2	$\hat{age}_\tau$	-0.23	0.10
ι_3	$\hat{W}$	0.03	0.02
ι_4	FB	1.10	0.72
ι_5	$AD\hat{L}TS$	0.10	0.33
σ_ι^2	variance of ϵ_ι	0.04	0.06
$\sigma_{\chi,\iota}$	covariance of ϵ_χ and ϵ_ι	-1.16	1.16

TABLE 5

CHOICE DISTRIBUTION BY WAVE, DEMONSTRATION

ACTUAL VS. PREDICTED (IN PARENTHESES)

		Wave[1]			
Index (*j*)	Choice	1 [89]	2 [88]	3 [84]	4 [79]
1	no services	3.4	34.1	67.9	70.9
		(3.9)	(28.4)	(56.8)	(76.0)
2	outpatient only	74.2	50.0	26.2	22.8
		(69.6)	(52.8)	(31.8)	(17.9)
3	outpatient and inpatient	3.4	1.1	1.2	1.3
		(4.9)	(3.9)	(2.4)	(1.6)
4	outpatient and non-residential	4.5	8.0	2.4	2.5
		(5.9)	(4.4)	(2.8)	(1.3)
5	outpatient, inpatient, and non–residential	2.3	0.0	1.2	0.0
		(1.6)	(1.1)	(0.6)	(0.3)
6	outpatient and residential	2.3	2.3	1.2	2.5
		(1.9)	(1.8)	(1.4)	(0.9)
7	outpatient, inpatient, and residential	1.1	1.1	0.0	0.0
		(1.3)	(1.2)	(0.9)	(0.5)
8	outpatient, non-residential, and residential	3.4	1.1	0.0	0.0
		(4.7)	(3.1)	(1.7)	(0.7)
9	outpatient, inpatient, non-residential, and residential	5.6	2.3	0.0	0.0
		(6.0)	(3.3)	(1.6)	(0.8)
	chi-square (8) value	1.7	8.0	7.3	6.3

1. Use occurs between Wave x and Wave x+1. The number of observations is in brackets.

TABLE 5

CHOICE DISTRIBUTION BY WAVE, COMPARISON

ACTUAL VS. PREDICTED (IN PARENTHESIS)

		Wave[1]			
Index (*j*)	Choice	1 [53]	2 [52]	3 [50]	4 [45]
1	no services	18.9	57.7	82.0	84.4
		(19.9)	(49.3)	(71.2)	(81.3)
2	outpatient only	47.2	34.6	12.0	13.3
		(52.3)	(32.9)	(18.8)	(11.7)
3	outpatient and inpatient	34.0	7.7	6.0	2.2
		(27.9)	(17.7)	(10.1)	(7.0)
	chi-square (2) value	1.0	3.7	2.9	1.6

[1.] Use occurs between Wave x and Wave x+1. The number of observations is in brackets.

TABLE 6

MENTAL HEALTH CHOICES OF DEMONSTRATION PARENTS,

BASELINE AND COUNTERFACTUAL EXPERIMENTS

	Choice	Simulation	Wave 1	Wave 2	Wave 3	Wave 4
(1)	No services	Baseline	3.9	28.4	56.8	76.0
(2)		No Intermediate Services[1]	3.2	25.3	52.4	71.7
(3)		Costly Services[2]	3.2	25.3	52.4	71.7
(4)		No Promotion[3]	14.7	43.2	66.1	80.3
(5)	Outpatient only	Baseline	69.6	52.8	31.8	17.9
(6)		No Intermediate Services	70.6	54.7	33.8	20.0
(7)		Costly Services	70.7	54.8	33.9	20.0
(8)		No Promotion	60.5	40.0	22.9	13.2
(9)	Outpatient and Inpatient, No Intermediate	Baseline	4.9	3.9	2.4	1.6
(10)		No Intermediate Services	26.2	20.0	13.8	8.4
(11)		Costly Services	26.0	19.9	13.7	8.3
(12)		No Promotion	24.8	16.8	11.0	6.6
(13)	Outpatient, Inpatient, and Intermediate	Baseline	9.0	5.6	3.1	1.5
(14)	Outpatient and Intermediate, No Inpatient	Baseline	12.6	9.3	5.9	3.0

1. See text for the details of the No Intermediate Services, Costly Services, and No Promotion experiments.

TABLE 7

MENTAL HEALTH CHOICES OF ALL PARENTS,

BASELINE AND PUBLIC POLICY EXPERIMENT

			Wave			
j	Choice	Simulation	1	2	3	4
1	No services	Baseline[1]	16.6	45.5	68.0	80.7
		Policy Experiment[2]	10.3	36.9	62.9	78.5
2	Outpatient only	Baseline	57.4	37.4	21.4	12.6
		Policy Experiment	63.7	45.9	27.0	15.9
3	Outpatient and Inpatient	Baseline	26.0	17.1	10.7	6.7
4	Outpatient and Non-Residential	Policy Experiment	7.8	5.3	3.3	1.8
6	Outpatient and Residential	Policy Experiment	3.7	3.3	2.5	1.6
8	Outpatient, Non-Residential, and Residential	Policy Experiment	14.5	8.5	4.4	2.1
4+6+8	Outpatient, and at least one Intermediate	Policy Experiment	26.0	17.1	10.2	5.5

1. For Comparison households, same as "Baseline" in Table 5. For Demonstration, same as "No Promotion" in Table 6.

2. Inpatient services are not available to any household but all households have access to costly Intermediate Residential and Non-Residential services. Each intermediate service costs $281.

FIGURE 1
Wave 1 (142 observations) and Wave 4 (73 observations)
Observed CBCL Distribution

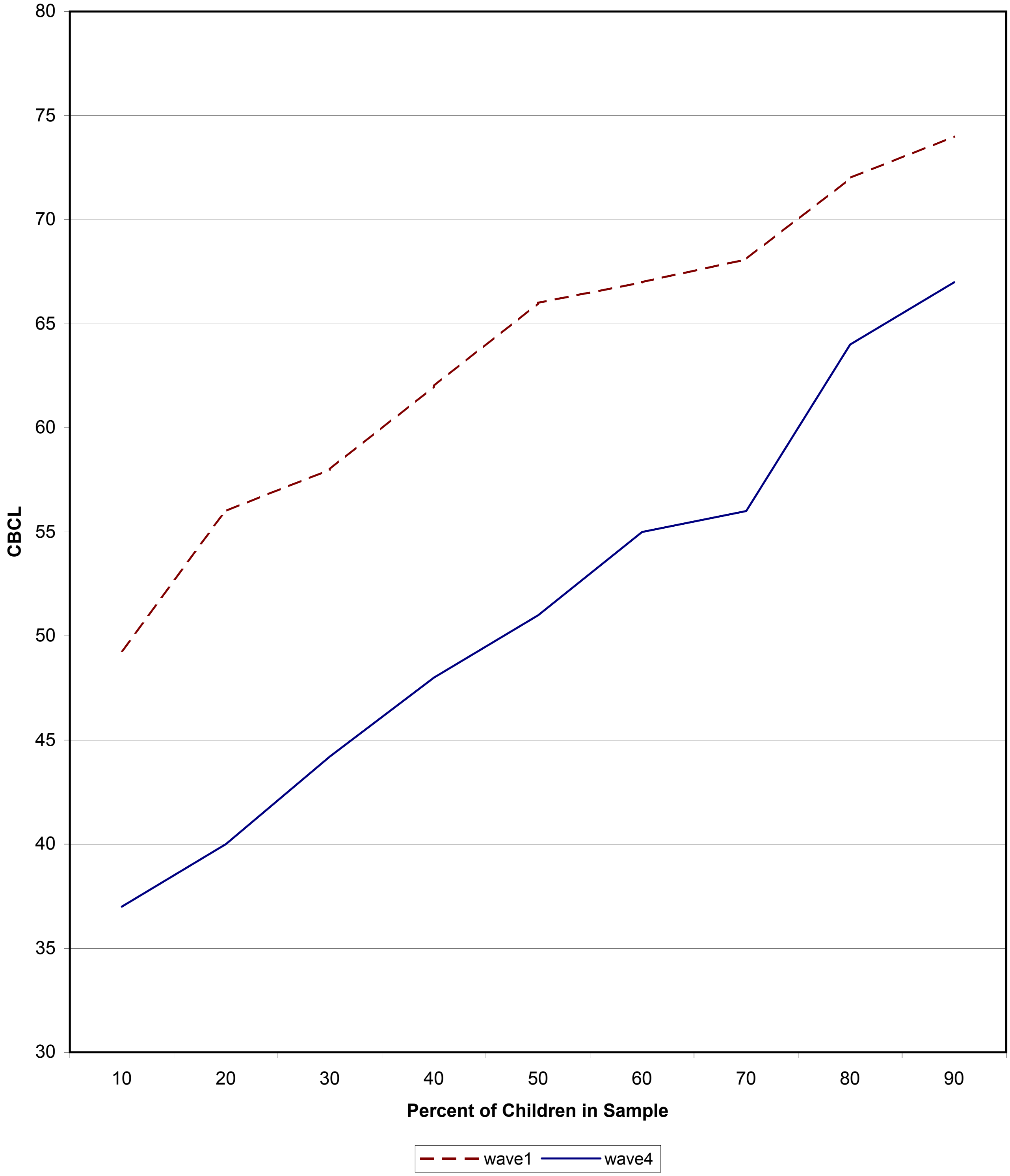

FIGURE 2
Wave 4 CBCL Distribution,
Data (73 observations)
and Model Predicted for only these 73 observations

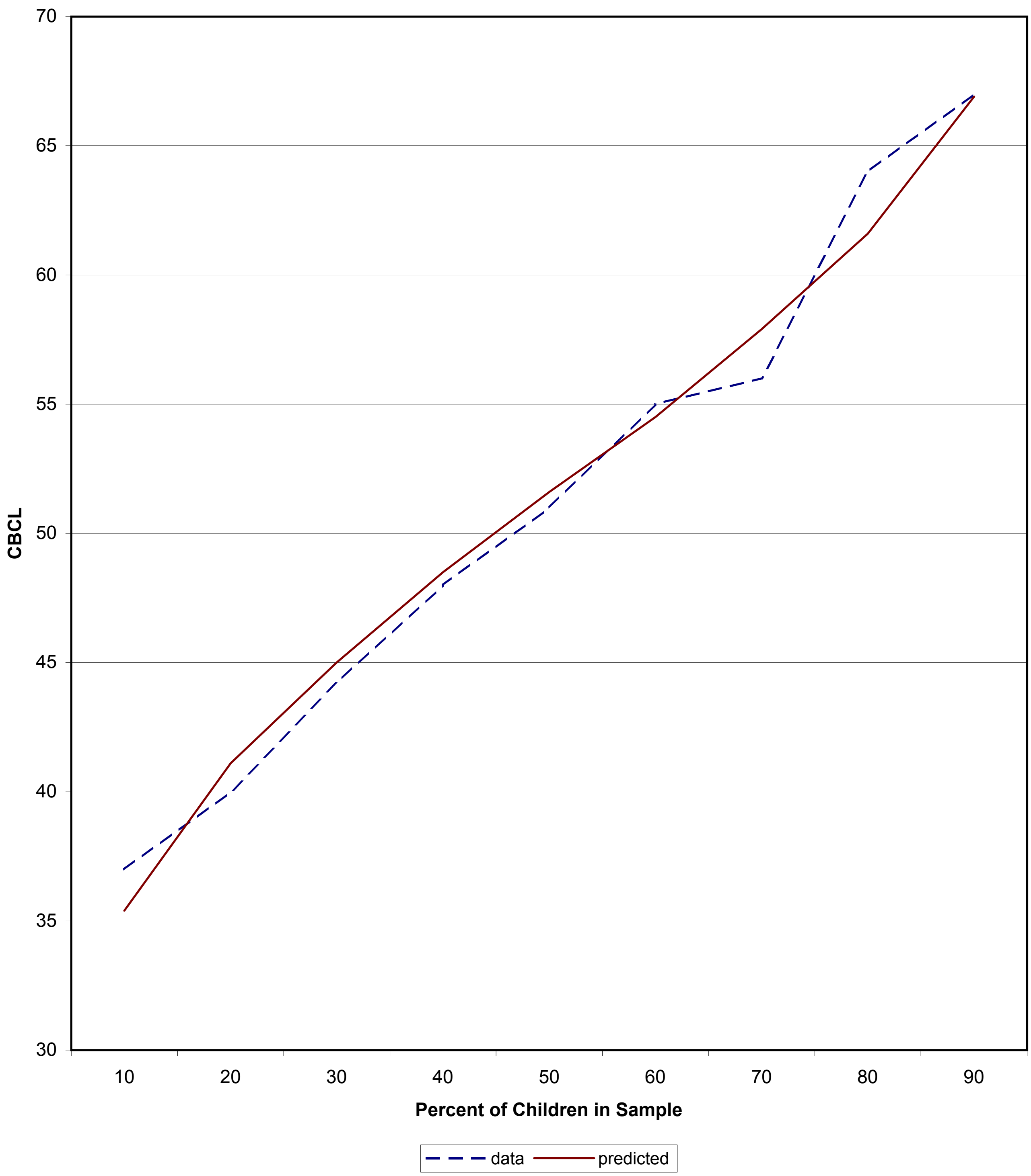

FIGURE 3
Simulated CBCL Distribution,
Baseline and No Services Experiment,
Entire Sample