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Welfare Effects of Fixed and Percentage-Expressed Child Support Awards

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Abstract

Over the last decade a large number of states have significantly altered their legal statutes concerning the disposition of divorce cases involving children. In particular, many states have increasingly employed percentage-expressed orders in which child support obligations in a given period are determined as a proportion of the contemporaneous income of the noncustodial parent. In contrast to more traditional systems in which obligations were set in fixed nominal terms at the time of the divorce settlement and were infrequently (or never) updated, the dynamic system has the advantages of allowing children (and the custodial parent) an opportunity to share in the general income gains experienced by the noncustodial parent over the life cycle and of possibly alleviating some noncompliance problems.

In this paper we conduct a rather extensive theory-based empirical investigation of the effects of these systems on the income process for divorced fathers and the child support transfer decision. We estimate a flexible statistical model for the income-generation process for divorced fathers which encompasses the period both before and after the divorce. We interpret the estimates from this model to indicate small behavioral effects of the type of order on postdivorce income, but nonrandom assignment (in terms of the means and variances of predivorce income) into the percentage-expressed-order state. Our analysis of the effects of the order type on child support transfers is divided into two parts. In the first, a "reduced form" analysis, we investigate whether or not the divorced father's regime—defined as the order type and withholding status—can be considered exogenous vis-á-vis the transfer decision, and examine the relative effects of the various regimes on the transfer rate. We further attempt to investigate order-type effects on compliance in the context of a structural model of the compliance decision. The results of the two analyses are for the most part consistent. Percentage orders are generally associated with lower compliance rates, though withholding tends to alleviate the problem. The highest compliance rates are associated with fixed orders coupled with withholding.

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1. INTRODUCTION

Child support issues have been actively researched and debated over the past several decades in response to the substantial decline in the welfare of children living with only one parent.[1] Recent changes in family structure have contributed to an increase in child poverty; nearly all of this increase can be attributed to the rising proportion of families headed by divorced or never-married mothers.[2]

The government does not allow noncustodial parents who have been ordered to pay child support to decide for themselves how much support they will pay; instead, it has authorized the courts to determine the amount that must be paid. Many custodial parents and children's advocates have protested that child support awards are often too low and that courts do not use a preestablished system to set the amount of payments. Economists and sociologists, therefore, have been searching for ways to improve the criteria used in setting child support orders.

Research on child support issues can be roughly divided into studies concerned with normative problems involving the distribution of welfare among divorced parents and their children and studies assessing the efficiency of various child support policies in achieving certain normative goals. Some examples of the first type of study include Betson et al. (1992), Garfinkel and Melli (1989), Garfinkel and Oellerich (1989), Garfinkel et al. (1990), Lazear and Michael (1988), Lerman (1989), Oellerich and Garfinkel (1983), and Williams (1987). In these analyses, the incomes of the parents before any child support payments are made are typically taken to be exogenously determined, and policies are evaluated in terms of their effects on those incomes. Problems of imperfect compliance and

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[1]Good general summaries of the scope of the divorce problem and empirical research on the effects of custody and child support negotiations and arrangements on the welfare of children and divorced parents are contained in Weitzman (1985) and Maccoby and Mnookin (1992).

[2]The proportion of children living with only one parent increased from 14.9 percent in 1970 to 25 percent in 1990 (U.S. Bureau of the Census 1991).

behavioral responses to child support orders (such as changes in labor supply, job turnover, or remarriage decisions) are not usually explicitly considered.

The primary focus of the second class of studies is the behavioral response of parents to child support orders and any income transfers associated with them. For example, Graham and Beller (1989), Maritato and Robins (1992), and Del Boca (1994) studied the effect of child support income on the labor supply of custodial mothers; Del Boca and Flinn (1994b) investigated the effect of the mix of child support and non–child support income of custodial mothers on their expenditures on "child-specific" goods; and Weiss (1984) studied the effect of divorce on the consumption patterns of single-parent households. Fewer studies have analyzed the behavioral responses of fathers or both parents to child support orders; some that have are Garfinkel and Klawitter (1990), Meyer and Bartfeld (1992), and Del Boca and Flinn (1990), all of which analyze the decision of whether to comply with child support orders.

The approach taken in the present paper is something of a hybrid, in the sense that the structure within which the empirical analysis is performed is dictated by theoretical considerations, but the econometric models utilized are designed for flexibility and ease of interpretation. Only in Section 6 is an explicit behavioral model estimated in order to determine the nature of the effects of order type on transfers (i.e., child support payments). In all other sections, we have attempted to fit models with as few restrictions built in as possible, and have concentrated on separating behavioral influences of order type from spurious relationships induced by systematic selection in the various order regimes.

The plan of the paper is as follows. Section 2 contains an informal description of some of the behavioral and welfare issues connected with the design of child support orders. In Section 3 we provide an overview of the data used in the three sections of empirical analysis included here. (Different subsamples from these data are utilized in the three sections, and the relevant subsample is described in more detail within each section.) In Section 4 we present the results of the estimation of a "treatment effects" model of order type on the income-generation process. Data on the personal income of divorced fathers (distinguished by the type of child support order they eventually receive) both before and after the divorce is used to determine the effects of awards on the mean and variance of their income processes. Section 5 contains estimates of the relationship between transfers, order amount, order type, and father's income in the year following the divorce. We test whether order type is endogenous in the child support regression function, and generally find evidence that it is not. We find that order type has large effects on transfers (also loosely interpretable as compliance, given the regression function specification we use), with fathers with fixed awards and routine withholding having the highest "compliance rates." Section 6 contains an analysis of the transfer decision within a behavioral model in which transfers and "compliance" are functions of the mother's and father's incomes and the level of the child support order, as well as preference parameters describing the weighting of the child's welfare in the father's utility function and the cost of noncompliance. We estimate the structural model for fathers with fixed and percentage-expressed orders separately, to determine whether fathers under the two regimes have different preferences and/or different costs of noncompliance. Section 7 offers a brief conclusion.

2. POLICY ISSUES

Until very recently, child support orders had been determined by judges on a case-by-case basis; thus, the amount of child support a custodial parent was awarded depended on a judge's discretion rather than an independent set of rules. The results were that two sets of parents in similar situations were often treated differently, and orders were often too low. The 1988 Family Support Act contains provisions that are changing the system as it was; it aims to increase the contribution of noncustodial parents to custodial parents and create support orders that are more appropriate and equitable. To meet these goals, the act does two things: it establishes a withholding system whereby child support payments are taken out of a custodial parent's paycheck (just as income taxes are);[3] and it requires that all states develop a set of rules to apply in all cases when determining the amount of an award.

One state, Wisconsin, did not wait for the Family Support Act to reform its child support system. Wisconsin established a percentage-of-income standard in 1983 that some judges began using the next year. In using this standard judges based the award amount solely on the income of the noncustodial parent and the number of children to be supported. The rule was to order 17% of the father's income if the parents had one child and 25%, 29%, 31%, and 34% respectively for two, three, four, and five or more children. This standard could have been overridden if the parents and the judge agreed on some mutually acceptable, privately determined order.

In July 1987 the percentage standard became presumptive in Wisconsin: judges have to use it unless they state in writing for the record why they are declining to use it. Between 1988 and 1991, the standard was used in 41.5% of paternity cases and in 58.5% of divorce cases (Meyer, Garfinkel, Bartfeld, and Brown 1994).

Judges can use the standard in three ways. They can calculate the dollar amount represented by the appropriate percentage of income (e.g., 17% if the custodial parent has only one child) and install it as a fixed dollar award. They can express the amount of an award simply as a percentage of the noncustodial parent's income, which means that the amount of the award will change with the noncustodial parent's income. And judges can create "hybrid" orders in which the monthly award is a percentage of income or a fixed amount, whichever is greater (Meyer et al. 1993). This type of order ensures that a custodial parent receives a minimum amount of transfer income even when the income

[3]Wage withholding of the child support obligation from wages has been used in some states in cases with a history of delinquent payments. By July 1987 all counties in Wisconsin were required to use withholding automatically from the time the award was issued.

of the noncustodial parent falls to a low level, and it makes it easier to determine if the noncustodial parent is defaulting on his or her child support obligations.

From the viewpoint of social science theory, it is not difficult to enumerate the differential effects of percentage-expressed and fixed orders on the behavior of divorced parents. Some of these issues concern order-type effects on the incomes of both parents (through their choices concerning their labor supply, their occupations, and their financial and human capital investments) and on compliance incentives in particular.[4]

First consider the issue of the labor supply of the noncustodial parent. If we view the earnings of the noncustodial parent as determined within a standard neoclassical labor supply framework, percentage orders will be "inefficient" in the sense that they will distort labor supply decisions. Let noncustodial parents make labor supply decisions according to the rule $h(w,y;s)$, where w is the market wage, y is their nonlabor income, and s is their child support obligation.[5] If expressed as a percentage, the child support obligation in effect becomes a tax on labor earnings, so that the noncustodial parent's labor supply decision is $h((1-\tau)w,y)$, where τ is the proportion of the noncustodial parent's income transferred to the mother. A percentage-expressed order thus has associated substitution and income effects, so the net effect of such an order on labor supply is generally ambiguous.[6] A fixed order of s, on the other hand, affects labor supply by effectively shifting the level of nonlabor income, so that labor supply will be given by $h(w,y-s)$. (In this case,

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[4]See Lerman (1989, 1990) and Betson et al. (1992) for general discussions and comparisons of different guidelines.

[5]For simplicity here we are implicitly describing a case in which the father derives no utility from the mother's expenditures on the child. The same general points made here will hold in a situation in which expenditures on the child increase both parents' welfare.

[6]Under certain assumptions about preferences, the effect of changes in τ on labor supply can be unambiguously signed. For example, when the noncustodial parent's preferences are Cobb-Douglas, increases in τ reduce his labor supply and child support transfers (the latter are given by $\tau wh((1-\tau)w,y)$).

labor supply is unambiguously nondecreasing when leisure is a normal good.) Percentage-expressed orders are inefficient in the sense that to obtain a transfer of s dollars to the mother, the percentage-expressed order will yield a *lower* utility value to the father than when the order is fixed.

This inefficiency is an important consideration for policymakers even when the goal of child support transfers is only to increase the welfare of custodial parents and children. This is the case since compliance with a percentage-expressed order yielding a transfer of s produces less utility than compliance with a fixed order of s. Therefore noncustodial parents may be less likely to comply with percentage-expressed orders than with fixed orders, and compliance of course directly affects the welfare levels actually attained by custodial parents and their children.

Percentage-expressed orders may also encourage noncustodial parents to choose riskier occupational or financial investments than they would under fixed-order schemes. Consider the choice between two occupations characterized by average earnings and standard deviation in earnings $(\bar{y}_j, \sigma_j),\ j = 1,2;$ assume for the purpose of discussion that earnings in each occupation are normally distributed so that the first two moments are sufficient to characterize the distribution completely. Neglecting labor supply considerations, let the father's contemporaneous utility function be given by $u(c)$, where c is his consumption.[7] Then his expected utility in occupation j under percentage orders is $\int u((1-\tau)y)d\Phi((y-\bar{y}_j)/\sigma_j),$ while under fixed orders his utility will be given by $\int u(y-s)d\Phi((y-\bar{y}_j)/\sigma_j)$. To compare occupational choices, let $\bar{y}_1 = \bar{y}_2,$ and compare the results of a percentage order τ with a fixed order $s = \tau\bar{y}_1$. Then on average the same amount is transferred under the percentage-expressed

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[7]Again we are neglecting the fact that child support transfers also typically are utility increasing (for the noncustodial parent) when expenditures on the child are a public good. While such considerations mitigate the force of the argument given here, they do not eliminate the relevance of the risk-transference issue in comparing fixed and percentage-expressed orders.

and the fixed order. When the noncustodial parent is risk-averse (so that *u* is concave), he will generally choose the "riskier" occupation under the percentage-expressed order, where risk here implies a larger standard deviation of earnings over time, because the percentage-expressed order will reduce the variation in posttransfer income. The custodial mother will thus receive the same average transfer under either regime, but will experience more variability in transfers under the percentage-expressed orders. If she is risk-averse, this increased variability will be viewed as a "bad."

On a more pragmatic level, noncompliance may be encouraged under percentage-expressed orders if the noncustodial parent can easily "hide" income from the custodial parent and/or child support officials. Compliance with a percentage-expressed order can only be determined after observing the noncustodial parent's income, so that there is a delay in assessing compliance and difficulties in accurate determination where the noncustodial parent has an incentive and opportunity to underreport income.

In terms of behavioral implications, fixed orders apparently have much to recommend them when compared to percentage-expressed orders. Arguments in favor of percentage-expressed orders stem mainly from normative and administrative considerations. Percentage-expressed orders offer indexing, which fixed orders do not. Obviously, the value of a fixed order of *s* dollars will be seriously eroded over a period of high inflation. At least as important as providing a hedge against inflation, indexing links the welfare of the members of the nonintact family in a direct manner. Since most divorced fathers are in the early part of their labor market careers, they usually experience substantial earnings growth following the divorce.[8] Percentage-expressed orders provide a mechanism to contemporaneously transfer the welfare gains attributable to earnings growth to the noncustodial parent and child.

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[8]Recent research using Wisconsin data documents substantial increases over time in the earnings of noncustodial parents (Phillips and Garfinkel 1992). As other research using national data has shown, custodial parents' incomes decline while noncustodial parents' incomes improve following divorce.

Fixed orders can also be changed over time to reflect substantial changes in the incomes of the fathers and expenditure requirements for the child; doing so, however, is costly for child support agencies and for the parents. Changing fixed orders requires court appearances, and in practice requires the custodial parent to initiate proceedings. Such actions may be costly for the custodial parent, both in terms of money and time requirements and in the possibility of upsetting the "equilibrium" of the relationship between the two ex-spouses. The dynamic and mechanical aspects of percentage-expressed orders are designed to minimize these costs.

In this section, we have provided a framework in which to interpret the empirical analyses that follow. In Section 4, we will be looking for effects of order type on the mean and variance of postdivorce earnings. We view the labor supply considerations discussed above as operative in explaining mean differences, while we think of the risk-transference issue as having the possibility of accounting for differences in income variability. In Sections 5 and 6 we empirically examine compliance issues. From the above arguments, and from earlier empirical analyses of the problem (e.g., Bartfeld and Garfinkel [1992]), we expect percentage-expressed orders to be associated with lower compliance rates due to enforcement problems. We will want to determine whether this is the case after allowing for endogeneity in order-type assignment and within a behavioral model in which the distribution of noncompliance costs can be directly estimated for fathers who must pay fixed orders and those who must pay percentage-expressed orders.

3. DATA

The data set from which all the samples are extracted is the Wisconsin Court Record Data (WCRD), which was constructed from randomly selected court records of paternity and divorce cases in twenty-one counties during the 1980s. The WCRD includes information on the cases themselves and on the parents, including age, income, and employment. Unfortunately, income information is missing in a substantial number of cases. The WCRD also contains complete information on the history of child support orders and payments. The data were collected over ten cohorts of individuals. Since we are interested in comparing fixed and percentage-expressed orders, we restrict our analysis to cohorts 7 and 8 (the petition dates of these cohorts range from 1986 to 1989), the first cohorts with a substantial number of cases with percentage-expressed orders.

We also use income data from the state income tax returns of the parents (the returns were provided by the Wisconsin Department of Revenue). These data are limited in the sense of being unavailable for individuals who have moved out of state, who have very low incomes, or who for other reasons were not required to file a state income tax return.

We use divorced cases that entered the courts between 1986–1989 in which there was a child support order with one parent designated as the payer; we use information on the parents' situations (e.g., income, age) at the time the support order was finally issued. Our selection results in 1468 cases, of which approximately one-fourth have percentage-expressed orders. For 151 cases the percentage order is 17 percent, for 129 it is 25 percent, and for 57 cases it is about 30 percent, which reflects the distribution of the number of children. Employment information is available for 1352 fathers and 1309 mothers; 89 percent of fathers are employed, as are 72 percent of mothers. A slightly larger proportion of the unemployed fathers than employed fathers have percentage-expressed orders (27.3 percent and 23.8 percent respectively). In the case of the mothers, 25 percent of the employed and 25 percent of the unemployed have percentage-expressed child support awards.

The source of the income data is the Wisconsin Department of Revenue. For the cohorts whose data we use, state income tax returns are available for *at most* the years 1986 through 1989. Unfortunately, a large number of fathers and mothers have missing income information. Income data are more likely to be missing in cases involving percentage-expressed orders.

In the overall sample, the use of percentage-expressed orders increased from 1986 to 1989. About 31 percent of cases were petitioned during 1986, another 50 percent of them in 1987, and the remaining cases in 1988. The share of percentage-expressed orders rose from 22 percent to 32 percent over these years.

Analyzing the issue of compliance with percentage-expressed orders is complicated and requires access to income data in order to impute the dollar amount of orders in a given year. Thus the presence of income tax data is required for an individual with a percentage-expressed order to be included in any sample used to study compliance. For individuals with fixed orders, this is not the case since the order amount is included in the administrative record which contains the amounts transferred. As did Bartfeld and Garfinkel (1992), in the study of compliance issues we only include individuals with fixed orders who also have income tax information. This is done to make the criteria by which we select our sample "symmetric" for the percentage-expressed and fixed-order cases.

Generally speaking, percentage-expressed orders are used more often in the case of younger noncustodial parents, which suggests that this type of order is used when the father's income is expected to increase. However, the most evident variation in order type seems to be at the county level. This suggests that the preferences of the judge or family court commissioner may strongly affect the types of orders issued, contributing to the substantial variation across counties. The county effects may also reflect differences in the administrative costs of determining compliance with percentage-expressed awards.

Different samples will be used in the empirical analyses reported in Sections 4, 5, and 6. We utilize all petition years for the analysis of the income-generation process of divorced fathers under the different regimes (Section 4). In this case, the only information used regarding orders and payments is order type (fixed or percentage-expressed). We restrict the sample to include fathers filing state income tax returns from 1986–1989, with the (possible) exception of the year in which the final decree was granted. In the "reduced form" analysis of compliance in Section 5, we include only fathers who filed a state income tax return in the year following the divorce. In Section 6 we use a sample that includes those cases in which state income tax returns were available *for both* divorced fathers and mothers in the year following the divorce.

4. THE INCOME-GENERATION PROCESS OF DIVORCED FATHERS

As was noted in the previous section, there are a number of possible effects of percentage orders and fixed orders on the income-generation process. Using a simple neoclassical labor supply model, it is easy to show that percentage orders, which operate as a tax on labor earnings, act to lower labor supply, earnings, and child support transfers in comparison with "equivalent" fixed orders.[9] Therefore, holding constant other individual differences, we would expect to find mean earnings among fathers with percentage orders to be lower than mean earnings among fathers with fixed orders.

We also argued above that risk-transference aspects of the two types of orders may be important considerations when comparing the welfare of the parents. The fact that percentage orders act as a way to transfer consumption risk from fathers to mothers may affect both the mean and variance of earnings of divorced fathers. It is not possible to precisely predict the nature of the effects without further assumptions on the occupational earnings distributions and preferences of parents.

In this section we fit a relatively general statistical model to predivorce and postdivorce income data for divorced fathers under percentage-expressed and fixed orders. The analysis is designed to shed light on the following issues:

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[9]Equivalent orders are defined in the following way. For any fixed order, F, determine the transfer $\hat{t} = \max\ (t^*, F)$ where t^* is the equilibrium expenditure in the absence of an order. Now define a percentage $\hat{\tau} = \hat{t}/(wh(w,F))$. Then the labor supply under the percentage order, which we will denote $h(\tau w)$, will be less than $h(w,F)$. Therefore the transfer and earnings will be less under the percentage-expressed order than the "equivalent" fixed order F.

(i) Do the predivorce income processes of fathers differ depending on whether they are ultimately assigned percentage-expressed or fixed orders? In particular, are there systematic differences in mean earnings, or in light of the risk-transference issues discussed above, are there systematic differences in income variation? Agents responsible for the determination of order type may be more likely to assign percentage-expressed orders to parents whose incomes vary little over time.

(ii) Do fathers with fixed orders have higher postdivorce mean earnings than fathers with percentage-expressed orders?

(iii) Does the order type affect the postdivorce variation in earnings of divorced fathers?

In order to describe the differences between the income processes of individuals in the percentage-expressed (*P*) and fixed-order (*F*) groups, we adopt the following relatively flexible specification of the income processes of fathers in the two groups which cover periods *both before* and after the order is assessed. Of course, these statistical models are restrictive in a number of ways or identification of the processes would not be possible given the crude data at hand.

The data available consist of income tax returns for (at most) the years 1986–1989. Our sample consists of fathers who were issued child support orders in the years 1986–1988. In describing the income-generation process, we always exclude the year of the divorce (i.e., child support order). Data on income in the year of the divorce is excluded for essentially two reasons. First, since we are interested in describing the predivorce and postdivorce income processes, income data from the year of the divorce consists of partial-year observations from the two regimes. Given the data available to us, there is no way to apportion the income into the two regimes. Second, it seemed likely that income from the divorce year would not be a "representative" draw from the income-generation process; using this information may introduce bias into the estimation of the parameters of the statistical model for "normal" earnings.

We will refer to fathers in our sample who received child support orders in year *t* as belonging to the *t* cohort. Individuals selected into the final sample satisfied the condition that data from state income tax returns were available for them in *all years* from 1986–1989 with the possible exception of the year of the child support order. Then an individual in cohort 1986 who is included in our sample has valid State of Wisconsin income data for the years 1987, 1988, and 1989. All the income observations from an individual in this cohort would be postdivorce. An individual from the 1987 cohort would have one observation (1986) on predivorce income and two (1988 and 1989) on postdivorce income. Finally, an individual from the 1988 cohort contributes two observations (1986 and 1987) on predivorce income and one on postdivorce income (1989). The income variable actually used in the analysis is the personal income of the individual in the calendar year. While this measure includes income from personally held assets, it predominately consists of labor earnings for virtually all individuals in the sample.

We represent the personal income of father *i* in year *s* by

$$\begin{aligned} &y_{is}^{\omega} = \beta_s + \vartheta_i^{\omega} + \varepsilon_{is}^{\omega} &&; \quad s < t \; ; \\ [4.1] \quad &y_{is}^{\omega} = \beta_s + \vartheta_i^{\omega} + \xi_{is}^{\omega} + \tau^{\omega} &&; \quad s > t \; ; \\ &i = 1,\ldots,n \;\; \omega \in \{P,F\} \; ; \; s \in \{86,87,88,89\}. && \end{aligned}$$

where

ϑ_i^{ω} is a time-invariant individual fixed effect; the index ω indicates that the distribution of the individual effects differs in the populations of fathers under fixed and percentage-expressed orders,

β_s is a period *s* effect common to all individuals,

τ^{ω} is the effect of order type ω on individual earnings postdivorce,

$\varepsilon_{is}^{\omega}$ is an i.i.d. disturbance associated with individual *i* who received an order of type ω in year *t* which follows s,

ξ_{is}^{ω} is an i.i.d. disturbance associated with individual *i* who received an order of type ω in year *t* which precedes *s*.

The following distributional assumptions have been made:

$$\vartheta_i^{\omega} \sim (\overline{\vartheta}^{\omega}, VAR(\vartheta^{\omega})) \quad \forall \quad i,$$

$$[4.2] \quad \varepsilon_{is}^{\omega} \sim (0,\ VAR\ (\varepsilon^{\omega})) \quad \forall \quad (i,s),$$

$$\xi_{is}^{\omega} \sim (0,\ VAR(\xi^{\omega})) \quad \forall \quad (i,s).$$

All of the parameters have been discussed with the exception of β_s, which represents period effects in this model. This parameter captures the effect of variables that vary deterministically over time (like the ages of the father, mother, and children) and aggregate shocks to the economy (in this case, economic conditions in the State of Wisconsin). The presence of the β_s and ϑ_i^{ω} obviate the need for introducing regressors into the model, since all potential regressors available to us either (i) vary deterministically in time or (ii) are time-invariant and are thus "absorbed" in the term ϑ_i^{ω}. For the purposes of this exercise, we are not interested in determining the separate effect of such variables on the income-generation process, and so we neglect them.

Methods of moments estimators were employed for all estimable functions of the parameters. These estimators, although less efficient than estimators that exploit more distributional assumptions on the data-generation process, are in our view preferable in data description exercises where relatively robust estimation is at a premium. The moment estimators we implement below are all consistent, though the estimators for variance parameters are biased in small samples. We note that our moment estimators are also inefficient with respect to the class of moment estimators proposed by Hansen (1982), which he terms "generalized moment estimators." In fact, we make no attempt to compute standard errors for any of the estimable functions, which is a necessary step in generalized method of moment estimation.

We now turn to issues of estimability of model parameters. Before proceeding to specific cases, we note that in general *several* estimators are typically available for any estimable moment. In such a case, we usually combine these estimators to produce one estimator. The combination of estimators we have chosen to produce the "unique" estimator of the parameter is arbitrary, typically being a function of relative sample sizes. For one case, the multiple estimators available for a parameter were so different that we decided not to combine them and instead have reported each of the estimates individually. While the estimates vary markedly, the general inference we draw concerning the income-generation process seems unaffected by which estimator we choose to focus on.

We first consider estimation of what would traditionally be referred to as the "treatment effects," the τ^P and τ^F. The model proposed here allows for several sorts of treatment effects of course, in that the distribution of the variances of the i.i.d. shocks after divorce is allowed to differ for the groups *P* and *F*. Now due to the presence of fixed individual effects and the period effects β_s, the τ^{ω}'s are not separately identified. However, the *difference* in the treatment effects is. To illustrate the methods employed in constructing estimators in this section, we will discuss our construction of this particular estimator in some detail.[10]

There exist four possible estimators of the function $(\tau^P - \tau^F)$ given our data. One estimator is

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[10]For surveys of issues related to the evaluation of welfare and training policies see Heckman and Robb (1985), Manski and Garfinkel (1992), and Barnow et al. (1980); this literature stresses identification issues when using quasi-experimental data.

$$[4.3] \quad (\tau^P \,\tilde{-}\, \tau^F)_A = \{ (\bar{Y}^P_{88}\ (87) - \bar{Y}^P_{86}\ (87)) - (\bar{Y}^F_{88}\ (87) - \bar{Y}^F_{86}\ (87)) \},$$

where $\bar{Y}^{\omega}_{s}(t)$ denotes the mean earnings of individuals in cohort t in year s with an order type of ω. Note that the expected value of this estimator is

$$[4.4] \quad E\left[(\tau^P \,\tilde{-}\, \tau^F)_A \right] = (\beta_{88} + \tau^P - \beta_{86}) - (\beta_{88} + \tau^F - \beta_{86})$$
$$= \tau^P - \tau^F ,$$

and the estimator is unbiased. Since it is a differentiable function of sample moments, each of which is a consistent estimator of its corresponding population moment, the estimator is consistent as well.

The three other estimators of this function of population moments are

$$[4.5] \quad (\tau^P \,\tilde{-}\, \tau^F)_B = \{ (\bar{Y}^P_{89}(87) - \bar{Y}^P_{86}(87)) - (\bar{Y}^F_{89}(87) - \bar{Y}^F_{86}(87)) \} , [4.6] \quad (\tau^P \,\tilde{-}\, \tau^F)_C = \{ (\bar{Y}^P_{89}(88)$$

$$[4.7] \quad (\tau^P \,\tilde{-}\, \tau^F)_D = \{ (\bar{Y}^P_{89}(88) - \bar{Y}^P_{87}(88)) - (\bar{Y}^F_{89}(88) - \bar{Y}^F_{87}(88)) \} .$$

We take a linear combination of these estimators to form an "unique" one. In this case, the weighting was as follows:

$$[4.8] \quad (\tau^P \,\tilde{-}\, \tau^F) = .5 \frac{n_{87}}{n_{87} + n_{88}} (\tau^P \,\tilde{-}\, \tau^F)_A + .5 \frac{n_{87}}{n_{87} + n_{88}} (\tau^P \,\tilde{-}\, \tau^F)_B$$
$$+ .5 \frac{n_{88}}{n_{87} + n_{88}} (\tau^P \,\tilde{-}\, \tau^F)_C + .5 \frac{n_{88}}{n_{87} + n_{88}} (\tau^P \,\tilde{-}\, \tau^F)_D .$$

Being a differentiable function of consistent estimators, it once again follows that [4.8] is consistent and will (generally) be at least as efficient as any of the individual estimators *A* through *D*.

The difference in the mean of the distribution of individual time-invariant effects for the two regimes $(\bar{\vartheta}^P - \bar{\vartheta}^F)$ is estimable. The estimator we utilize is essentially a combination of three individual estimators for this function:[11]

$$[4.9] \quad (\bar{\vartheta}^P \tilde{-} \bar{\vartheta}^F)_A = \frac{1}{3} \Big[\{ \bar{Y}^P_{87}(86) + \bar{Y}^P_{88}(86) + \bar{Y}^P_{89}(86) - \bar{Y}^F_{87}(86) + \bar{Y}^F_{88}(86) + \bar{Y}^F_{89}(86) \} - 3(\tau^P \tilde{-} \tau^F) \Big],$$

$$[4.10] \quad (\bar{\vartheta}^P \tilde{-} \bar{\vartheta}^F)_B$$

$$- \bar{Y}^F_{86}$$

and

$$[4.11] \quad (\bar{\vartheta}^P \tilde{-} \bar{\vartheta}^F)_C = \frac{1}{3} \Big[\{ \bar{Y}^P_{86}(88) + \bar{Y}^P_{87}(88) + \bar{Y}^P_{89}(88) - \bar{Y}^F_{86}(88) + \bar{Y}^F_{87}(88) + \bar{Y}^F_{89}(88) \} - (\tau^P \tilde{-} \tau^F) \Big].$$

We use the following linear combination of these three consistent estimators:

$$[4.12] \quad (\bar{\vartheta}^P \tilde{-} \bar{\vartheta}^F) = \frac{n_{86}}{n_{86} + n_{87} + n_{88}} (\bar{\vartheta}^P \tilde{-} \bar{\vartheta}^F)_A + \frac{n_{87}}{n_{86} + n_{87} + n_{88}} (\bar{\vartheta}^P \tilde{-} \bar{\vartheta}^F)_B + \frac{n_{88}}{n_{86} + n_{87} + n_{88}} (\bar{\vartheta}^P \tilde{-} \bar{\vartheta}^F)_C .$$

While only differences in mean effects can be identified due to the presence of period effects, it is possible to individually identify all the variances

[11]Actually, each of these three estimators is composed of one *or more* consistent estimators of this function. The three estimators specified here are distinguished by the fact that each is a function of the data for a specific divorce cohort only.

which appear in [4.2]. We have constructed an estimator for the postdivorce shocks for the percentage-expressed and fixed-order regimes from a weighted average of three available estimators. For regime ω, the three estimators are

$$[4.13]\quad \tilde{VAR}(\xi^{\omega})_A = .5\ VAR(y_{i,89} - y_{i,88} \mid i \in \omega,\ i \in C_{87}),$$

$$[4.14]\quad \tilde{VAR}(\xi^{\omega})_B = .5\ VAR(y_{i,89} - y_{i,88} \mid i \in \omega,$$

and

$$[4.15]\quad \tilde{VAR}(\xi^{\omega})_C = .5\ VAR(y_{i,88} - y_{i,87} \mid i \in \omega,\ i \in C_{86}),$$

where C_s denotes the set of sample members (each indexed by *i*) belonging to divorce cohort *s*, and the *VAR* functions on the right-hand sides of [4.13]–[4.15] are sample variance functions. The weighted average estimate we report is determined by

$$[4.16]\quad \tilde{VAR}(\xi^{\omega}) = \frac{n_{87}^{\omega}}{n_{87}^{\omega} + 2n_{86}^{\omega}}\ \tilde{VAR}(\xi^{\omega})_A + \frac{n_{86}^{\omega}}{n_{87}^{\omega} + 2n_{86}^{\omega}}\ \tilde{VAR}(\xi^{\omega})_B + \frac{n_{86}^{\omega}}{n_{87}^{\omega} + 2n_{86}^{\omega}}\ \tilde{VAR}(\xi^{\omega})_C.$$

We have also computed three estimators for the variance of the predivorce shocks (ε^{ω}). The estimates produced by these three estimators varied widely in our sample, so we have not reported a single estimate of this population moment. The three estimators utilized (three for each regime ω, recall) are

$$[4.17]\quad \tilde{VAR}(\varepsilon^{\omega})_A = .5\ VAR(y_{i,87} - y_{i,86} \mid i \in \omega,\ i \in C_{88}),$$

$$[4.18]\quad \tilde{VAR}(\varepsilon^{\omega})_B = VAR(y_{i,88} - y_{i,86} \mid i \in \omega,\ i \in$$

and

$$[4.19]\quad \tilde{VAR}(\varepsilon^{\omega})_C = VAR(y_{i,89} - y_{i,86} \mid i \in \omega,\ i \in C_{87}) - \tilde{VAR}(\xi^{\omega}).$$

Finally, we utilize these estimators to form an estimator of the variation in the "fixed effects" by treatment group. Conditional on consistent estimates of the variances of the predivorce and postdivorce shocks by treatment group, we distinguish three estimators of $VAR(\vartheta^{\omega})$. They are:

$$[4.20] \quad \tilde{VAR}(\vartheta^{\omega})_A = \frac{1}{9}\left\{ VAR(y_{i,87} + y_{i,88} + y_{i,89} \,|\, i \in \omega,\ i \in C_{86}) - 3\ \tilde{VAR}(\xi^{\omega})\right\},$$

and

$$[4.21] \quad \tilde{VAR}(\vartheta^{\omega})_B = \frac{1}{9}\left\{ VAR(y_{i,86} + y_{i,88} + y_{i,89} \,|\, i \in \omega,\ i \in C_{87}) - 2\ \tilde{VAR}(\xi^{\omega}) - \tilde{VAR}(\xi^{\omega})\right\},$$

The weighted average estimator of the variance of the fixed effect utilized is

$$[4.22] \quad \tilde{VA}$$

$$[4.23] \quad \tilde{VAR}(\vartheta^{\omega}) = \frac{n^{\omega}_{86}}{n^{\omega}_{86} + n^{\omega}_{87} + n^{\omega}_{88}}\ \tilde{VAR}(\vartheta^{\omega})_A + \frac{n^{\omega}_{87}}{n^{\omega}_{86} + n^{\omega}_{87} + n^{\omega}_{88}}\ \tilde{VAR}(\vartheta^{\omega})_B + \frac{n^{\omega}_{88}}{n^{\omega}_{86} + n^{\omega}_{87} + n^{\omega}_{88}}\ \tilde{VAR}(\vartheta^{\omega})_C .$$

Because we have three estimates for the predivorce shock variance and the estimator in [4.23] is a function of this particular variance estimate, we report three estimates produced by [4.23], each corresponding to one of the three estimates of that parameter.

The method of moments estimates appear in the second column of Table 4.1, and a number of interesting patterns in the income processes of divorced fathers emerge. First note that the differences in the standard mean-shifting "treatment" effects between percentage-expressed and fixed orders is negligible. The average income (in 1986 dollars) of fathers in the entire sample is approximately $23,000 dollars, so that the difference in treatment effects of -356 is less than 2 percent of average income.

TABLE 4.1

Methods of Moments Estimates of the Income-Generation Process, by Order Type

Parameter	Estimator Defined In	Point Estimate
$\tau^P - \tau^F$	[4.8]	-355.799
$\bar{\vartheta}^P - \bar{\vartheta}^F$	[4.12]	-3333.041
□ $\boldsymbol{VAR}(\varepsilon^P)$		
(*A*)	[4.17]	19670.423
(*B*)	[4.18]	6222.016
(*C*)	[4.19]	5912.994
□ $\boldsymbol{VAR}(\varepsilon^F)$		
(*A*)	[4.17]	5036.781
(*B*)	[4.18]	8764.308
(*C*)	[4.19]	9749.291
□ $\boldsymbol{VAR}(\xi^P)$	[4.16]	4708.506
□ $\boldsymbol{VAR}(\xi^F)$	[4.16]	7667.166
□ $\boldsymbol{VAR}(\vartheta^P)$		
(*A*)	[4.23]	11913.595
(*B*)	[4.23]	13450.379
(*C*)	[4.23]	13465.975
□ $\boldsymbol{VAR}(\vartheta^F)$		
(*A*)	[4.23]	17898.657
(*B*)	[4.23]	17758.606
(*C*)	[4.23]	17708.695

The fact that no treatment effects exist does not mean that mean earnings in the two treatments are the same. We find that the difference in the mean fixed effects in the two groups is -3333, approximately ten times the size of the treatment effect difference. Thus, while individuals with percentage orders have significantly lower incomes than those with fixed orders postdivorce, the differential is essentially maintained in the predivorce periods. On the basis of this evidence we conclude that mean differences in the incomes of these groups are attributable to selection and not to the order type per se.

The estimates of the standard deviations of the predivorce shocks display marked differences across the two groups, though there is a large degree of instability of estimates across the three estimators employed for each group. The estimator which is defined over differences only (estimator *A*) produces an estimate of the standard deviation of the shock in the percentage-expressed group which is roughly four times the size of the corresponding moment in the fixed-order group. However, the other two estimators examined produce estimates of the standard deviation which are much larger in the fixed-order group than in the percentage-order group. While we have not developed any formal basis on which to compare the estimates, we have somewhat more confidence in the estimates not based on differencing (the estimates obtained from estimators *B* and *C*). We shall come back to an interpretation of these results after discussing the other variance estimates.

The standard deviation of the postdivorce shocks is significantly greater in the fixed-order group than in the percentage-expressed group (7667 versus 4709). If divorced fathers with percentage-expressed orders had an incentive to choose income-generation processes (jobs and/or investment activities) with larger variances, we would expect to see the variance of the postdivorce shock to increase relative to its predivorce level. In fact, the standard deviation of the postdivorce shock is quite a bit less than its predivorce counterpart for percentage-order cases (from 19670, 6222, or 5913 down to 4709). Thus there is no evidence that fathers with percentage orders choose riskier income-generation processes, at least in the first few years after the divorce. The reduction in the standard deviation of the earnings shock also occurs for fathers with fixed orders, at least under the two estimates of this moment produced by estimators *B* and *C*.

The estimates of the variance of the individual effects in the two populations of fathers also display easily noticeable differences. All of the estimates of the standard deviations of the ϑ^P are no more than 75 percent as large as corresponding estimates of the standard deviations of the ϑ^F. Taken together, the estimates of all of the standard deviations in the model indicate significantly more dispersion in all of the random variables describing the dynamic income distribution of fathers with fixed orders.

As was the case in the interpretation of the differences in means results, our estimates of the variance components also seem to indicate a significant degree of selection in terms of order-type assignment, with little behavioral effect of the program itself. The fathers with large amounts of variability in their earnings processes are more likely to be given fixed orders than are those with more stable earnings. If institutional actors have limited information about the father's income history so that it is impossible for them to disentangle ϑ and ε, this selection mechanism also explains why the variance in the ϑ terms is greater for fathers under fixed orders. Selection-type arguments thus seem to account for most of the results in Table 4.1, though why the variance of income shocks in the postdivorce period is so much smaller than in the predivorce period (for both groups) remains somewhat of a mystery.

5. REDUCED-FORM MODELS OF COMPLIANCE BEHAVIOR

In this section we examine the relationship between the characteristics of the child support order, which include whether it is percentage expressed or fixed, whether withholding is in effect, the size of the order, and the amount transferred from the father to the mother. The analysis contained here is based on a simple econometric specification of the relationships between these characteristics and transfers, and any attempt at explaining the mapping from order type to transfers in a behavioral manner is postponed until Section 6. Nonetheless, in this empirical model we will examine some issues relating to the possible endogeneity of the order characteristics in the child support transfer regression function. The model specified here has the advantages of simplicity of statistical interpretation of the results and comparability with previous empirical analyses in the literature.

For the moment, assume that all divorced fathers in the sample make positive child support transfers, t, to the mothers. Denote the income of fathers by y_f and the amount ordered by s. Let P denote the indicator variable which is equal to 1 iff the father has a percentage-expressed order, and let $F \equiv 1\text{-}P$. Similarly let W denote the indicator variable which is equal to 1 iff withholding is in effect, and let $N \equiv 1\text{-}W$. We specify the transfer rule by

$$[5.1] \quad \ell n(t) = \beta_1 \boldsymbol{P}\cdot W + \beta_2 \boldsymbol{P}\cdot N + \beta_3 F\cdot W + \beta_4 F\cdot N + \psi_1 \ell n(s)\cdot \boldsymbol{P}\cdot W + \psi_2 \ell n(s)\cdot \boldsymbol{P}\cdot N + \psi_3 \ell n(s)\cdot F\cdot W + \psi_4 \ell n(s)\cdot F\cdot N + \eta\ \ell n(y_f) + z\gamma + u \ ,$$

where z is a row vector of observable covariates, γ is a conformable column vector, and u is a disturbance term which is mean-independent of all right-hand-side variables with the possible exception of the indicator variables for order type $\{P,F\}$ and withholding status $\{W,N\}$.

Unlike the functions estimated by other researchers, the regression function we use has a few unusual characteristics. First, note that aside from the indicator variables, the relationship between t, s, and y_f is linear in the logarithms. From the point of view of examining compliance behavior, such a specification has a potentially serious defect and one real strength. The defect is that the transformation of the dependent variable, $\ell n(t)$, is not defined for cases in which the father makes no transfer. While this would be a serious problem if one were examining *monthly* transfer amounts, it is not a serious problem in our data. First, the time unit of analysis is the year, and the proportion of fathers who make no transfers over the year in the population of divorced fathers with child support orders is relatively small. Second, this proportion is even smaller in the population of Wisconsin fathers filing state income tax returns in the year following the divorce. From an original sample size of 489 fathers, only 27 made no transfers over the year and were therefore excluded from the following analysis.

Specification [5.1] has the advantage that the effects of orders on transfers, represented by the ψ coefficients, have the interpretation of elasticities. Then the elasticity of transfers with respect to orders clearly depends on which "regime" a father is in. Thus we can compare elasticities in a straightforward way across regimes. For example, an increase of 1 percent in child support orders for a father with percentage-expressed orders and subject to withholding results in an increase in transfers of ψ_1 percent. We will loosely interpret these elasticities as "compliance rates," as seems natural.

Besides being expressed in logarithms, [5.1] differs from other specifications used to empirically determine the effect of percentage-expressed orders on transfers. For example, Bartfeld and Garfinkel (1992) specify a regression function relating levels of transfers as a function of regime and levels of orders, but do not include an interaction term between the two. While misspecification of the relationship between orders, transfers, and regimes could possibly produce an essentially "independent" effect of regime type on transfers, the global interpretation of such an effect presents a problem.[12] Clearly, we should expect the regime type to affect the rate of compliance with an order of size s. In the regression function specification, this implies that an interaction term between the two is the appropriate specification.

Given specification [5.1], we will be interested in testing for regime effects under the full model and in two special cases. The special cases correspond to situations in which (1) there are no interactions between the regime and the order amount (consistent with most previous empirical

[12] For example, the coefficients reported in Table 8 of Bartfeld and Garfinkel imply that having a percentage-expressed order increases the transfer by 111 dollars for *any* size order.

analyses of this issue) and (2) there are interaction effects with the order amount but no independent effects of regime on the amount transferred. Since the general specification nests the two special cases, it will be sufficient to specify the nature of the restrictions tested using [5.1].

We first test whether or not there are percentage-expressed order effects on transfer amounts given withholding effects. In this case, the restrictions tested are

$$[5.2] \qquad \mathcal{H}_0^P : \begin{aligned} \beta_1 &= \beta_3 \\ \beta_2 &= \beta_4 \\ \psi_1 &= \psi_3 \\ \psi_2 &= \psi_4, \end{aligned}$$

so there are four in all under the full model, two restrictions ($\beta_1 = \beta_3$ and $\beta_2 = \beta_4$) when the slope parameter ψ is restricted to be the same across regimes, and two restrictions ($\psi_1 = \psi_3$ and $\psi_2 = \psi_4$) when the constant term β is restricted to be the same across regimes. As in all the cases considered in this section, the alternative hypothesis is no restrictions on the regression parameters.

The restriction of no withholding effects given percentage-expressed-order effects is given by

$$[5.3] \qquad \mathcal{H}_0^W : \begin{aligned} \beta_1 &= \beta_2 \\ \beta_3 &= \beta_4 \\ \psi_1 &= \psi_2 \\ \psi_3 &= \psi_4. \end{aligned}$$

As was the case above, there are four restrictions under the full model and two each under the restricted models.

Finally, the null of no regime effects is given by

$$[5.4] \qquad \mathcal{H}_0^R : \begin{aligned} \beta_1 &= \beta_2 \\ \beta_1 &= \beta_3 \\ \beta_1 &= \beta_4 \\ \psi_1 &= \psi_2 \\ \psi_1 &= \psi_3 \\ \psi_1 &= \psi_4. \end{aligned}$$

In this case there are six restrictions in the full model and three each in the restricted versions.

Prior to estimating the model, testing for regime effects, and comparing elasticities, it is necessary to consider the potential problem of endogeneity. In what follows we will always consider the amount of the order to be exogenous with respect to the transfer decision. This assumption is a practical necessity since this data set has a dearth of potential instrumental variables. Therefore, we only consider the possibility that the regime may be endogenous. We first will examine the issue of endogeneity of the order type conditional on the assumption of exogenously determined withholding status. We then consider the endogeneity of withholding status conditional on the assumption of exogenously determined order type. Finally, we test for endogeneity of order type and withholding status simultaneously. The reader should bear in mind that the instrumental variable procedures utilized below are strictly valid only under the assumption that the regime and the amount of child support ordered are statistically independent.

To construct instruments for the regime type we use a simple index function approach. For example, consider the case in which the order type is endogenous but withholding status is exogenously determined. Then let the father be given a percentage-expressed order iff

[5.5] $\boldsymbol{P}^{*} = x_1\lambda_1 + v_1 \geq 0,$ where x_1 is a row vector of observable characteristics of the father, λ_1 is a conformable column vector of unknown parameters, and v_1 is i.i.d. $N(0,1)$. Then the probability that a father is given a percentage-expressed order is simply $\Phi(x_1\lambda_1)$, where Φ denotes the standard normal cumulative distribution functions. Maximum likelihood estimates of λ_1 are easily obtained from any univariate probit procedure.

Next consider the case in which order type is exogenously determined but withholding status is endogenous in [5.1]. In this case a father is assumed to be subject to withholding iff

[5.6] $W^{*} = x_2\lambda_2 + v_2 \geq 0,$

where v_2 is i.i.d. $N(0,1)$. The probability of withholding is $\Phi(x_2\lambda_2)$, and maximum likelihood estimates of λ_2 are straightforward to compute.

Finally consider the case in which *both* order type and withholding status are endogenously determined. In such a case [5.5] and [5.6] are estimated simultaneously under the assumption that the error terms are i.i.d. bivariate normal, where

[5.7] $\begin{bmatrix} v_1 \\ v_2 \end{bmatrix} \sim N\left(\begin{bmatrix} 0 \\ 0 \end{bmatrix}, \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right).$ Instruments are included in [5.1] in the following manner. When only order type is considered endogenous, all occurrences of the variable P are replaced with $\hat{\boldsymbol{P}} = \boldsymbol{\Phi}(x_1\hat{\lambda}_1)$ and F is replaced with $1-\hat{\boldsymbol{P}}$, where $\hat{\lambda}_1$ is the maximum likelihood estimate of λ_1 from the univariate probit model. When only withholding status is considered endogenous, all occurrences of *W* are replaced with $\hat{W} = \Phi(x_2\hat{\lambda}_2)$ and *N* is replaced with $1-\hat{W}$, where $\hat{\lambda}_2$ is the maximum likelihood estimate of λ_2 from the univariate probit model with withholding status as the dependent variable. When both order type and withholding status are considered endogenous, we use the following instruments for regime type:

$$[5.8] \quad \begin{aligned} \hat{P \cdot W} &= \Phi_2(x_1\hat{\lambda}_1, x_2\hat{\lambda}_2, \hat{\rho}) \ , \\ \hat{P \cdot N} &= \Phi_2(x_1\hat{\lambda}_1, -x_2\hat{\lambda}_2, -\hat{\rho}) \ , \\ \hat{F \cdot W} &= \Phi_2(-x_1\hat{\lambda}_1, x_1\hat{\lambda}_2, -\hat{\rho}) \ , \\ \hat{F \cdot N} &= \Phi_2(-x_1\hat{\lambda}_1, -x_2\hat{\lambda}_2, \hat{\rho}) \ , \end{aligned}$$

where $\Phi_2(\cdot,\cdot,\rho)$ is the bivariate standard normal cumulative distribution function indexed by correlation coefficient ρ, and $(\hat{\lambda}_1, \hat{\lambda}_2, \hat{\rho})$ are maximum likelihood estimates from the bivariate probit model.

It is of both substantive and technical interest to investigate the endogeneity issue even in this reduced-form model. The endogeneity issue is interesting substantively in that it sheds light on the nature of the selection mechanism, which in this case involves the behavior of institutional actors and divorced parents. This particular approach to looking at the selection issue has not been utilized previously in addressing the question of the effect of order characteristics on transfers and/or compliance.[13] Pragmatically, it is of interest to determine whether it is necessary to use instrumental variables, since due to the lack of good potential instruments there is likely to be a large loss in efficiency if they are used in situations where they are not required for purposes of consistency.

[13]Bartfeld and Garfinkel utilize an inverse Mills ratio approach to correct for selection, though this approach is valid under more stringent conditions on the joint distribution of the disturbances in [5.1] and [5.7] than are required under the procedure we utilize. Furthermore, they treat withholding status as exogenous throughout.

To test for endogeneity we use the "omitted variable" method developed by Durbin (1954), Wu (1973), and Hausman (1978) and nicely described in Godfrey (1988). The endogeneity test amounts to adding the estimated regime probabilities to specification [5.1] and then performing a test to determine whether all the coefficients associated with the predicted probabilities are jointly equal to zero. For example, when we consider the situation in which withholding status is taken to be exogenous with order type (potentially) endogenous, we estimate

$$[5.9] \quad \ell n(t) = \beta_1 \boldsymbol{P}\cdot W + \beta_2 \boldsymbol{P}\cdot N + \beta_3 F\cdot W + \beta_4 F\cdot N + \psi_1 \ell n(s)\cdot \boldsymbol{P}\cdot W + \psi_2 \ell n(s)\cdot \boldsymbol{P}\cdot N + \psi_3 \ell n(s)\cdot F\cdot W + \psi_4 \ell n(s)\cdot F\cdot N + \eta\ \ell n(y_f) + \alpha_1 \hat{\boldsymbol{P}}\cdot W + \alpha_2 \ell n(s)\cdot \hat{\boldsymbol{P}}\cdot W + u$$

by ordinary least squares (OLS).

Using the Eicker-White heteroskedasticity-consistent standard errors, we then test whether the OLS estimates of α_1 and α_2 are jointly equal to zero. If there is little evidence to reject this null, we conclude that it is likely that order type is not endogenous. The reader should bear in mind that the test is likely to have relatively low power when the quality of the instruments utilized is poor, as is the case here. Similar specifications are estimated and tests conducted for the withholding-only endogenous case and the joint endogeneity case.

For the reduced-form compliance estimates, we utilize a sample of divorced fathers who satisfied the following criteria: (1) received child support orders in 1986, 1987, or 1988; (2) filed a State of Wisconsin income tax return for the year following the one in which they received their child support order; (3) had child support order information for the calendar year following the receipt of the order; (4) had valid child support transfer information for the year following the divorce; and (5) made positive transfers to the mother during the year following the divorce. Prior to imposing condition (5) there were 489 valid cases from the WCRD; imposition of (5) resulted in a small loss of 27 cases.

Descriptive statistics for this sample are contained in Table 5.1. First note from a comparison between columns 1 and 2 of the table that the proportion of percentage-order cases is virtually identical both before and after cases with zero transfers are excluded. On the other hand, cases with withholding are slightly overrepresented when we impose the positive transfer requirement, which seems reasonable. In column 2, we see that approximately 22 percent of the individuals in the sample have percentage-expressed orders (100 cases). The majority of cases, 79 percent, are subject to mandatory withholding. The ratio of average transfers to average orders is approximately .88. The ratio of average orders to average income is about .20. Note that all monetary amounts expressed throughout the paper are denominated in terms of 1986 dollars.

Columns 3 and 4 of the table give sample statistics for the percentage-expressed and fixed-order groups. A larger proportion of fathers with percentage-expressed orders are subject to withholding. For the percentage-expressed cases, average orders are slightly higher while average incomes are slightly lower (which is known from the estimates in Section 3). In other respects, such as age and number of children, the fathers in the two regimes are similar. Fathers with

TABLE 5.1

Descriptive Statistics for Reduced-Form Compliance Analysis Sample

Variable	Total Sample	Sample with $t > 0$	Sample with $t > 0$: Percentage	Sample with $t > 0$: Fixed
Percentage order	0.217	.216	1.000	0.000
Withholding	0.773	.790	0.880	0.765
Transfer amount	3867.710 (3303.196)	4093.745 (3259.265)	4029.327 (3134.456)	4111.540 (3296.909)
Order amount	4664.799 (4179.269)	4672.494 (4060.110)	5214.710 (3460.815)	4522.710 (4202.652)
Father's income	23642.349 (18180.103)	23518.872 (17394.809)	21882.416 (11710.961)	23970.932 (18650.437)
Mother's age	31.063 (6.666)	31.119 (6.638)	29.650 (6.122)	31.525 (6.725)
Father's age	33.376 (7.220)	33.450 (7.224)	32.280 (6.717)	33.773 (7.334)
Number of children	2.045 (1.105)	2.067 (1.030)	2.080 (1.070)	2.064 (1.020)
Ln Transfer		7.994 (0.914)	7.990 (0.896)	7.996 (0.920)
Ln Order		8.185 (0.754)	8.365 (0.653)	8.135 (0.773)
Ln Father's income		9.896 (0.584)	9.867 (0.516)	9.904 (0.602)
Sample size	489	462	100	362

percentage-expressed orders are slightly younger, which may be related to the increasing trend in percentage-expressed-order awards over this period (1986–1988).

Table 5.2 contains probit estimates of regime probabilities. Column 1 contains univariate probit estimates of the model in which the dependent variable is the percentage-expressed-order indicator. The logarithm of the father's income in the year *following* the divorce is used in the estimation exercise, because this is the only income variable included in this extract. Since Section 4 demonstrated that there is no systematic effect of order type on the mean level of the income process, this income measure is probably a reasonably good proxy for the father's income at the time the child support award was determined. We see that conditional on parental ages and number of children, there is a positive relationship between income and the probability of a percentage-expressed order, though the effect is not statistically significant. The only parameter estimate more than twice its standard error is the age of the mother, which is negatively related to the receipt of a percentage-expressed order.

Column 2 contains estimates of the univariate probit model in which the withholding indicator is the dependent variable. Fathers with higher incomes are more likely to be subject to withholding, quite possibly because they have more stable employment patterns and thus are easier to subject to withholding in the first place. Fathers with larger numbers of children are also more likely to be subject to withholding.

Columns 3 and 4 contain estimates from the bivariate probit specification. The pattern of the coefficient estimates of λ_1 and λ_2 is virtually unchanged from the univariate results. The error term in the latent variable expression for percentage-expressed orders, v_1, is positively correlated with the error term in the latent variable expression for withholding, v_2. Furthermore, the correlation coefficient is statistically different from zero at conventional significance levels. Allowing for a

TABLE 5.2

Probability of Percentage Order and/or Withholding: Univariate and Bivariate Probit Estimates (n = 462)

	Percentage Order Only	Withholding Only	Both	
			Percentage	Withholding
Constant	-0.523 (1.022)	-0.786 (1.066)	-0.498 (1.398)	-0.756 (1.106)
$ln(y_f)$	0.052 (0.112)	0.217 (0.116)	0.048 (0.152)	0.214 (0.120)
age_m	-0.496 (0.230)	0.002 (0.022)	-0.050 (0.023)	0.003 (0.022)
age_f	0.017 (0.020)	-0.026 (0.020)	0.018 (0.020)	-0.026 (0.020)
# kids	0.086 (0.070)	0.118 (0.073)	0.083 (0.070)	0.123 (0.073)
ρ	--	--	.248 (.095)	
$\mathcal{L}$	-236.876	-232.790	-466.477	

nonzero correlation between the v's significantly improves the predictive power of the model, which is especially important for the construction of good instruments.

As indicated above, we used the probit estimates to construct instruments for the variables that indicate regime. These instruments were used in conducting endogeneity tests, and the results are reported in Table 5.3. Generally speaking, we found little evidence of endogeneity in the nine specification tests run. To interpret the results, consider the entry in column 1, row 3, which corresponds to the test of percentage-order endogeneity *given* withholding-status exogeneity when the full model is estimated. The "full model" corresponds to specification [5.1] in which regimes can have effects both on the intercept and the slope (with respect to $\ell n(s)$) in the $\ell n(t)$ function. In this case [5.9] was estimated, and the null of exogeneity implies two restrictions on this equation. The test statistic was found to be 2.824, which is distributed as a $\chi^2_{(2)}$ random variable under the null. The probability of this value is .244, indicating that percentage orders, given exogenous withholding, are best considered exogenous in the transfer regression.

Across all six specifications in which regimes can affect constants or slopes but not both (the first two rows of Table 5.3), there is no evidence of endogeneity. Only when the regime can shift both the constant *and* the slope parameter is there any indication of endogeneity. In particular, the test for joint endogeneity of order type and withholding status in the full model produces a test statistic of 19.576, which has a probability of only .003 under the null of joint exogeneity. Aside from the results of this particular test, however, there is little evidence of endogeneity of regime type in the transfer regression. Therefore, we will focus our attention on the interpretation of the estimated version of [5.1] when instruments are not used.

Regression results are reported in Table 5.4. In the first column, OLS estimates of the restricted model in which regime type only shifts the intercept in the $\ell n(t)$ regression function are presented. Note that the coefficient associated with $\ell n(s)$ is .879, holding constant the father's

TABLE 5.3

Endogeneity Tests of Percentage Order and/or Withholding:
Test Statistics with Degrees of Freedom in [ ] and Probability under Exogeneity in ( )

	Instrumented Variable(s)		
Regime Effects	Percentage Order	Withholding	Both
Constants only	2.083	0.013	2.320
	[1]	[1]	[3]
	(0.149)	(0.910)	(0.509)
Slopes only	2.276	0.077	1.170
	[1]	[1]	[3]
	(0.131)	(0.781)	(0.760)
Constants and slopes	2.824	4.709	19.576
	[2]	[2]	[6]
	(0.244)	(0.095)	(0.003)

TABLE 5.4
OLS Regressions of *Ln*(*t*)
(Eicker-White Standard Errors)

	1	2	3
Constant		-0.978	
		(0.536)	
$P*W$	-1.077		-0.268
	(0.537)		(0.740)
$P*N$	-1.349		-2.593
	(0.569)		(1.498)
$F*W$	-0.852		-1.745
	(0.551)		(0.532)
$F*N$	-1.090		0.049
	(0.532)		(0.995)
$\ell n(y_f)$	0.177	0.182	0.210
	(0.066)	(0.065)	(0.064)
$\ell n(s)$	0.879		
	(0.048)		
$\ell n(s)*P*W$		0.861	0.743
		(0.047)	(0.095)
$\ell n(s)*P*N$		0.830	0.991
		(0.050)	(0.176)
$\ell n(s)*F*W$		0.890	0.948
		(0.048)	(0.052)
$\ell n(s)*F*N$		0.858	0.696
		(0.051)	(0.115)
<u>Tests of Regime Effects</u>			
No percentage order effect	10.510	11.125	14.325
	[2]	[2]	[4]
	(0.005)	(0.004)	(0.006)
No withholding effect	10.938	11.491	16.565
	[2]	[2]	[4]
	(0.004)	(.003)	(.002)
No percentage order or withholding effect	25.193	27.721	39.421
	[3]	[3]	[6]
	(<0.001)	(<0.001)	(<0.001)

income. Under our interpretation, a 1 percent increase in the ordered amount results in an .88 percent increase in transfers to the mother. Also, for every 1 percent increase in the father's income the transfer amount increases by .18 percent, holding constant the order. This is interesting because the standard order percentage for fathers with one child is 17 percent. One interpretation of this estimate is that this is the proportion of their income divorced fathers would choose to contribute to the mother even given ordered amounts.

In column 2 we present the estimates of the restricted model in which the regime only affects the elasticity of payments with respect to orders, or loosely speaking, the compliance rate. Note that the highest "compliance rate" (.89) is associated with fixed orders and withholding, while the lowest (.83) is associated with percentage-expressed orders without withholding. (This latter group comprises less than 3 percent of this sample.) Percentage orders with withholding and fixed orders without withholding have approximately the same coefficients.

The regression estimates in column 3 indicate that among the more precisely estimated regime effects (that is, excluding the regime $P{\cdot}N$), the fixed order with withholding regime continues to be the highest compliance regime. In terms of effects of the regime on the intercept, fixed orders without withholding have the largest coefficient.

The test statistics for the various regime effects are reported at the bottom of the table. In general, the tests reveal strong regime effects no matter what the specification of the test. The characteristics of the order are an important determinant of the amount transferred.

Table 5.5 contains estimation and testing results when the regimes are replaced with instruments. Because the instruments are relatively poor, all estimates are quite imprecise (that is, have large associated standard errors). Due to this fact, it is difficult to compare the results in this table with those in Table 5.4. Since there was little evidence for endogeneity, we believe that the results in Table 5.4 better reflect the reduced-form relationship between transfers, order regimes,

TABLE 5.5
OLS Regressions of *Ln*(*t*) with Instruments for Regimes
(Eicker-White Standard Errors)

	1	2	3
Constant		-0.629	
		(0.713)	
$P\hat{*}W$	-1.696		-9.590
	(1.131)		(11.074)
$P\hat{*}N$	4.623		-17.369
	(6.081)		(62.958)
$F\hat{*}W$	0.153		4.223
	(0.975)		(3.286)
$F\hat{*}N$	-2.156		-4.655
	(1.047)		(8.276)
$\ell n(y_f)$	0.164	0.173	0.172
	(0.075)	(0.076)	(0.078)
$\ell n(s)$	0.841		
	(0.047)		
$\ell n(s){*}P\hat{*}W$		0.725	1.714
		(0.151)	(1.350)
$\ell n(s){*}P\hat{*}N$		1.432	4.175
		(0.822)	(8.138)
$\ell n(s){*}F\hat{*}W$		0.912	0.355
		(0.078)	(0.432)
$\ell n(s){*}F\hat{*}N$		0.665	1.082
		(0.169)	(1.115)
<u>Tests of Regime Effects</u>			
No percentage order effect	3.484	1.719	15.780
	[2]	[2]	[4]
	(0.175)	(0.423)	(0.003)
No withholding effect	1.554	0.823	4.726
	[2]	[2]	[4]
	(0.460)	(.663)	(.317)
No percentage order or withholding effect	3.485	1.722	16.559
	[3]	[3]	[6]
	(0.323)	(0.632)	(0.011)

order amounts, and father incomes. On the basis of these results, we conclude that the effects of order regime on the transfers and welfare levels of divorced parents should concern shapers of child support policy.

6. BEHAVIORAL MODELS OF CHILD SUPPORT TRANSFERS UNDER PERCENTAGE-EXPRESSED AND FIXED ORDERS

The evidence from the reduced-form analysis of the compliance decision generally supported the idea that there were lower levels of compliance with percentage-expressed orders than fixed orders, holding the income of the custodial parent and the child support order constant, at least when both were combined with withholding. We also found that the effect of order type on transfer cannot be captured solely through intercept terms. In this section we estimate a structural model of child support transfers with a nontrivial compliance decision. This work extends our earlier research on compliance (Del Boca and Flinn 1993) to consider the differential effects of order type on the transfer process. Using this model, in principle we can determine whether fathers with percentage-expressed orders differ from fathers with fixed orders in terms of their relative preferences for own versus child consumption and/or in terms of the distribution of costs of noncompliance. The implications of the previous section's results appear to be that the preference characteristics of the fathers are not significantly different in the two order regimes (indicated by the lack of significance of the endogeneity tests of order type in the transfer regressions), but that the costs of noncompliance vary by regime. We will be interested in determining whether the structural model estimates are consistent with this interpretation.

To motivate our analysis, we first present the empirical distributions of child support awards and payments in the data utilized below. All amounts are expressed in monthly terms and in 1986 dollars. In Figure 6.1 we present the distribution of child support orders in our sample of 282 fathers

(222 with fixed orders and 60 with percentage-expressed orders). Figure 6.2 contains the distribution of actual child support transfers from the noncustodial father to the custodial mother; with respect to the distribution of orders, it tends to be "compressed" toward the origin. Figure 6.3 contains the distribution of the ratio of payments to orders. This distribution is interesting in that while the spikes at 0 and 1 (corresponding to what we will refer to later as *exact* compliance) are its predominate feature, a significant proportion of individuals make positive payments less than the amount ordered and a smaller proportion make payments greater than the ordered amount. The model we describe and estimate below will be able to capture these qualitative features of the distribution in a parsimonious manner.

Figures 6.4 through 6.6 are analogous to 6.1 through 6.3 but refer solely to the subsample of fathers with percentage-expressed orders. Because this sample is so small, it is difficult to draw many strong conclusions from these histograms, though it does appear that the distribution of transfers is a bit more "compressed" toward the origin than was the case for the entire sample. This impression persists when we compare it with the corresponding histograms for the subsample of fathers with fixed orders, which are contained in Figures 6.6 through 6.9.

Throughout the analysis, we will assume that the mother is the custodial parent. We begin by examining the behavior of divorced parents in an environment without child support orders. Though the divorced parents no longer inhabit the same household and are assumed to have access to two independent sources of income, denoted y_m and y_f, their welfare is connected after the divorce due to the presence of the public good, the child. Let c_p denote the private consumption of parent p, and let k denote the consumption of the child. Then the utility function of parent p is assumed to be Cobb-Douglas, so

$$[6.1] \quad u_p = \delta_p \, \ell n(c_p) + (1-\delta_p) \, \ell n(k), \; \delta_p \in [0,1], \; p \in \{m,f\} \; .$$

Figures 6.1 through 6.3 here

Figures 6.4 through 6.6 here

Figures 6.7 through 6.9

A critical assumption concerns the manner in which the consumption level of the child is set. Because the mother has both physical and legal custody, we assume that all "significant" expenditures on the child must be made or approved by her. We take the extreme position that the only way in which the father may augment the consumption level of the child is by transferring money to the mother. Given the father's transfer and her own income, the mother freely allocates it on her own consumption and that of the child.[14]

Without loss of generality, we will normalize the price of the private consumption goods of the parents and the child to unity. Given her total income level $y_m + t$, where t is the transfer from the father, the mother then chooses a level of expenditure on the child equal to $k*(\delta_m, y_m + t) = (1 - \delta_m)(y_m + t)$. The father, taking the mother's behavior as predetermined, chooses his transfer to the mother according to:

$$[6.2] \quad t*(\delta_m, \delta_f, y_m, y_f) = \underset{t \in [0, y_f)}{\boldsymbol{arg\ max}}\ \delta_f\ \ell n(y_f - t) + (1 - \delta_f)\ \ell n((1 - \delta_m)(y_m + t)).$$

Due to the functional forms with which we are working, it is also easily seen that the optimal transfer of the father to the mother is independent of the value of the mother's preference parameter, so $t*(\delta_f, y_m, y_f) = t*(\delta_m, \delta_f, y_m, y_f)$ for all values of δ_m. The decision rule is characterized by

$$[6.3] \quad t*(\delta_f, y_m, y_f) = \begin{cases} y_f - \delta_f y_t & if \quad \delta_f < y_f/y_t \\ 0 & if \quad \delta_f \geq y_f/y_t \end{cases},$$

where $y_t = y_m + y_f$ is aggregate parental income. The assumption that only mothers can directly make expenditures on "child goods" leads to the prediction that we would observe positive

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[14]In a dynamic model, the mother's choices in any period t may elicit behavioral responses from the father in later periods which she would consider in setting expenditure levels for period t. In such a situation, we might observe different choices of expenditure levels on child consumption by custodial mothers with the same levels of total income but different amounts of child support income (see Flinn [1994]). However, in a static model such as the one analyzed here, such feedback is ruled out and mothers have no behavioral or legal reason for treating the two income sources differently in making expenditure decisions.

transfers from fathers to mothers even in the absence of child support awards. Because the amount of the child support award appears nowhere in the specification, this model of transfers leads to no interesting implications regarding compliance behavior. To rectify this situation, we modify the preferences of the father so as to produce the utility function

$$[6.\prime 1] \quad u_f = \delta_f \, \ell n(c_f) + (1-\delta_f) \, \ell n(k) - \vartheta \, \mathbb{I}\,[t < s],$$

where s is the order, $\mathbb{I}\,[\zeta]$ is an indicator function which takes the value 1 when logical expression ζ is true and 0 when it is not, and ϑ is a fixed cost that the father pays if he does not fully comply with the order.[15] The penalty may be in the form of income reductions (due to fines, interest payments on child support owed, and/or the loss of work time due to incarceration) or in the reduction of time spent with the child.

Let us now examine the utility levels in states of exact compliance and the utility when the transfer $t*$ is made. Whether "exact" compliance occurs or not depends solely on the sign of the difference between the utility of noncompliance and compliance $V_n(\delta_m, \delta_f, \vartheta) - V_c(\delta_m, \delta_f)$. We will examine this difference for five qualitatively distinct cases, distinguished by values of the father's preference parameter δ_f and the noncompliance cost parameter ϑ. For reference, we also present a more formal characterization of these cases in Figure 6.10.

We first consider the case in which the father's preference parameter is greater than or equal to his share of total parental income, that is, the case of maximum "selfishness." In this case, if there were no noncompliance cost, the father would choose to transfer nothing to the mother. Then if the father does not comply with the order, he will transfer zero. If he chooses to comply (because the

[15]The addition of this type of random variable to account for differential levels of program participation or noncompliance within a homogeneous population is common in the literature (see, e.g., Moffitt [1983]).

FIGURE 6.10

Utilities and Transfers under Different Choices

Father's Preferences	Utility	Transfer
$1 > \delta_f > y_f/y_t$	$V_c = \delta_f \ell n(y_f - s) + (1-\delta_f) \ell n(y_m + s) + (1-\delta_f) ln(1-\delta_m)$	s
	$V_n = \delta_f \ell n(y_f - t^*) + (1-\delta_f) \ell n(y_m + t^*) - (1-\delta_f) ln(1-\delta_m) - \vartheta$	0
Choice depends on:	$0 \gtrless V_c - V_n$	
$(y_f - s)/y_t < \delta_f < y_f/y_t$	$V_c = \delta_f \ell n(y_f - s) + (1-\delta_f) \ell n(y_m + s)$	s
	$V_n = \delta_f \ell n(y_f - t^*) + (1-\delta_f) \ell n(y_m + t^*) - \vartheta$	$0 < t^* < s$
Choice depends on:	$0 \gtrless V_c - V_n$	
$\delta_f < (y_f - s)/y_t$	$V_n = \delta_f \ell n(y_f - t^*) + (1-\delta_f) \ell n(y_m + t^*)$	$t^* > s$

noncompliance cost ϑ is large), he will transfer the minimum amount necessary to avoid the noncompliance cost, which is the order *s*. Then for any value of δ_f in the interval $[y_f / y_t, 1]$, there exists a unique value of the noncompliance cost $D_0(\delta_f)$ such that for any value of ϑ greater than $D_0(\delta_f)$, the father will transfer *s*; for $\vartheta \leq D_0(\delta_f)$, the father will transfer nothing. These are the first two qualitatively distinct cases.

The next two cases correspond to the situation in which the father's preference parameter lies in the interval $[(y_f - s)/y_t, y_f / y_t]$. In this case, even if the noncompliance cost is zero, the father would choose to transfer a positive amount to the mother, *but an amount less than the order* s. Once again, for any value of δ_f in this interval, there will exist a unique value $D_1(\delta_f)$ such that if $\vartheta > D_1(\delta_f)$, the father will avoid the noncompliance cost and transfer the order *s*; if $\vartheta \leq D_1(\delta_f)$, the father will transfer a positive amount less than the order. In this latter case, we will say that the father "partially" complies.

The final case is the simplest to describe. If $\delta_f \leq (y_f - s)/y_t$, the father would optimally choose to transfer at least the amount of the order. Thus the child support order is not a binding constraint from the point of view of the father, and fathers in this situation will be said to "overcomply."

Figure 6.10 provides a summary of the three cases for a given parental income distribution (y_m, y_f) and a given order *s*. It is clear that if the distribution of δ_f in the population has support equal to [0,1], and if the cost of noncompliance parameter ϑ is sufficiently "dispersed" (in a sense to be made precise below), this model of the transfer decision in principle has the capability to explain the observed fact of the simultaneous existence of no transfers, partial compliance, exact compliance, and overcompliance evidenced in the data.

The sample can be thought of as being comprised of four classes of individuals, which are [*C1*] those fathers making no payment in the year, or $t = 0$; [*C2*] those fathers "partially complying" in the sense of making a transfer which is positive but less than the stipulated amount, or $0 < t < s$; [*C3*] those fathers making a payment exactly equal to the stipulated amount, or $t = s$; and [$C4$] those fathers "overcomplying" in the sense of making a transfer which is greater than the stipulated amount, or $t > s$. The contributions of members of these groups to the sample likelihood function are presented in Appendix A.

With all the required pieces defined, the sample log likelihood function is given by

$$\mathcal{L}(\psi_G, \psi_H) = \sum_{\{t=0\}} \ell n(L_{C1}) + \sum_{\{0<t<s\}} \ell n(L_{C2}) + \sum_{\{t=s\}} \ell n(L_{C3}) + \sum_{\{t>s\}} \ell n(L_{C4}),$$

where ψ_G is a finite-dimensional parameter vector which completely determines the distribution function of the preference parameter δ_f in the population of noncustodial fathers, and with ψ_H denoting the finite-dimensional parameter vector which completely characterizes *H*.

The model is completely characterized by the parameters which describe the distributions of the father's preference parameter and the direct cost of noncompliance. Let $\psi \equiv (\psi_G' \ \ \psi_H')'$. Then the maximum likelihood estimate of the parameter vector ψ is given by $\hat{\psi} = \arg \sup_{\psi \in \Omega} \mathcal{L}(\psi)$, where Ω is the parameter space, the characteristics of which are determined by the functional forms of the distribution functions *G* and *H*.

For the econometric model to be logically consistent, we must restrict our choice of *G*, the distribution of the direct cost of noncompliance, to those parametric distributions which have support on the positive real line. Similarly, our choice of *H* must come from the set of parametric distributions which have support on the unit interval. Pragmatically, the distributions we choose must be characterized by a very low dimensional parameter vector if we are to have any hope of precisely estimating the parameter vectors characterizing the distributions. This is especially true with respect to the distribution of ϑ, since this random variable is never directly observed. In the case of the random variable δ_f, its value is directly imputable for the portion of the sample which partially complies or overcomplies; for this reason, we can expect precise estimation of ψ_H to be an easier task than for ψ_G when ψ_G and ψ_H are similarly dimensioned.

We have estimated the econometric model under the assumption that the distribution of the father's preference parameter δ_f is of the form of a two-parameter beta. A beta distributed random variable takes values on the interval [0,1], and the distribution is quite "flexible." We assume that the distribution of the cost of noncompliance ϑ is exponential (and so is characterized by one parameter).

Under these distributional assumptions, the log likelihood function $\mathfrak{L}$ is characterized by three parameters, and the parameter space $\Omega = \mathbb{R}^3_+$. The log likelihood is continuously differentiable over the interior of the parameter space, and all standard regularity conditions for consistency and asymptotic normality of the maximum likelihood estimator of θ will be satisfied provided that the true parameter vector ψ_0 is an interior point of Ω. While $\mathfrak{L}(\psi)$ is not globally concave over Ω, we found that the maximum likelihood estimates reported below were attained no matter which point in Ω was used as a starting value in the optimization algorithm.[16]

Descriptive statistics for the sample used in this section are presented in Table 6.1. Characteristics of this sample are broadly consistent with those of the sample used in the reduced-form compliance analysis. The additional sample selection requirement that the mother also file a state income tax return has resulted in a sample with a slightly higher mean income (for the fathers) and slightly higher order amounts.

Because the data on orders and transfers are highly time-aggregated, and because the structural parameter estimates from this model of compliance tend to be quite sensitive to the proportion of the sample which "exactly" complies, we estimated the model after defining individuals with transfer/order

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[16]For each of the four sets of model estimates reported below, between five and ten diverse starting values were used.

ratios within a small interval around 1 as "exact" compliers. That is, for a given value of ε, we transformed the amount recorded as transferred according to the rule

$$[6.4] \quad \hat{t} = \begin{cases} t & \text{iff } t/s \notin [1-\varepsilon,\ 1+\varepsilon] \\ s & \text{iff } t/s \in [1-\varepsilon,\ 1+\varepsilon] \end{cases},$$

TABLE 6.1

Descriptive Statistics for Structural Compliance Analysis Sample

Variable	Total Sample	Sample with $t > 0$: Percentage	Fixed
Percentage order	0.213	1.000	0.000
Withholding	0.798	0.917	0.766
Transfer amount	4056.653	4068.416	4053.473
	(3134.510)	(2918.134)	(3196.748)
Order amount	5073.690	5425.010	4978.737
	(4607.411)	(3288.482)	(4905.300)
Mother’s income	14347.358	13243.844	14645.605
	(8454.004)	(8454.004)	(8120.027)
Father’s income	25050.568	23428.523	25488.958
	(12723.677)	(12723.677)	(20702.718)
Number of children	2.096	2.050	2.108
	(1.068)	(0.928)	(1.104)
Sample size	282	60	222

where $\hat{t}$ is our modified transfer used in the estimation exercise. Varying ε can of course have large effects on the estimates obtained.

Prior to applying [6.4] to the raw data, we consider the distribution of the sample in the interval $[1-\varepsilon, 1+\varepsilon]$ for various values of ε. Table 6.2 reports the numbers and proportion of individuals according to different ratios of transfers to orders. Only five individuals (under fixed orders) can be classified as perfect compliers for $\varepsilon = 0$. When we widen the interval from .95 to 1.05, we find 18 percent of the percentage-order and 41 percent of the fixed-order cases. When ε increases to .25 these percentages increase to 52 and 76 respectively.

Table 6.3 presents the estimates of the structural compliance model, when "exact" compliance is defined as $t/s \in [.95, 1.05]$. Four specifications are presented for the estimates of the distributions of δ_f and ϑ. Under specification *I*, separate distributions for the noncompliance cost and preference parameter distribution are estimated for the fixed-order and percentage-expressed-order groups. The point estimates indicate that the fathers are not very different in their preference characteristics, but that noncompliance costs are on average lower in the population of fathers with percentage-expressed orders.

Under specification *II*, the preference distributions are restricted to be the same in the two populations, while the noncompliance cost distributions are allowed to differ. In specification *III* the noncompliance cost distribution is restricted to be the same but the preference parameter distributions are allowed to differ. Finally, in *IV* all distributions are restricted to be the same. A comparison of the likelihood values indicates that there is virtually no statistically significant difference in the preference *and* noncompliance cost distributions for the two groups. This is a negative result from the perspective of consistency with our earlier findings, but one that was not totally unexpected a priori. The structural model relies on rather intricate nonlinearities in the data for identification of the behavioral distributions. With so few observations, sixty in the case of the percentage-expressed-order

TABLE 6.2

Numbers and Percentage of Individuals in Structural Estimation Sample with *t/s* Ratio in Selected Intervals

t/s Interval	Number of Individuals	Percentage of Sample
[1.000, 1.000]	5	0.018
	[0]	[0.000]
	(5)	(0.023)
[0.975, 1.025]	71	0.252
	[5]	[0.083]
	(66)	(0.297)
[0.950, 1.050]	102	0.362
	[11]	[0.183]
	(91)	(0.410)
[0.900, 1.100]	147	0.521
	[15]	[0.250]
	(132)	(0.595)
[0.850, 1.150]	172	0.610
	[23]	[0.383]
	(149)	(0.671)
[0.750, 1.250]	200	0.709
	[31]	[0.517]
	(169)	(0.761)

Notes: N = 282. Percentage orders are in [ ]; fixed orders are in ( ).

TABLE 6.3

Estimates of Structural Compliance Model, with Exact Compliance Defined as *t/s* ε [.95, 1.05]

	Specification					
	I		*II*	*III*		*IV*
Parameter	*P*	*F*	*P*	*F*	*P*	*F*
Distribution of the Father's Cobb-Douglas Utility Parameter (δ_f)						
ψ_1	2.717 (1.251)	3.520 (0.631)	**3.296** **(0.549)**	1.392 (0.417)	3.543 (0.628)	**3.294** **(0.549)**
ψ_2	1.851 (1.115)	1.672 (0.388)	**1.626** **(0.353)**	2.546 (1.154)	1.690 (0.387)	**1.625** **(0.353)**
$E(\delta_f)$	0.595	0.678	0.670	0.353	0.677	0.670
$SD(\delta_f)$	0.208	0.188	0.193	0.215	0.187	0.193
Distribution of the Noncompliance Cost Parameter (ϑ)						
ψ_3	2.006 (1.699)	1.329 (0.425)	1.634 (1.236)	1.340 (0.426)	**1.664** **(0.975)**	**1.375** **(0.410)**
$E(\vartheta)$	0.499	0.752	0.612	0.746	0.601	0.727
$\mathfrak{L}$	-623.614		-624.833		-623.714	-624.861

Note: Restricted parameters are in boldface.

group, lack of statistical significance is not surprising. Our conjecture is that if the sample size were increased to more reasonable levels, say on the order of 1000, statistically significant differences in the noncompliance cost distribution, and possibly the preference distribution, would emerge. Since the statistically insignificant differences here are broadly consistent with results from Section 5, we view the two exercises as complementary.

Table 6.4 repeats the estimation exercise for the case in which "exact" transference is defined for all *t/s* ratios in the interval [.9,1.1]. Since there is more "compliance" by definition in this sample, it is not surprising to see that the estimates reflect a shift in the noncompliance cost distribution toward larger values. This occurs for both percentage-expressed and fixed orders. On the other hand, the preference parameter distribution is relatively unaffected by the change in the definition of noncompliance. Statistical tests across the four specifications in Table 6.4 yield the same conclusions as we drew from Table 6.3. Distributional differences are statistically insignificant, but the costs of noncompliance appear quite a bit higher for fathers with fixed orders.

7. CONCLUSIONS

In this paper we have investigated the effects of fixed and percentage-expressed child support orders on the income of noncustodial fathers and child support transfer decisions. The results of the statistical model of the income-generating process of fathers before and after divorce show small effects of the type of order on postdivorce income, but indicate nonrandom assignment of the type of order.

The evidence from the reduced-form analysis of the compliance decision generally supported the idea that there were lower levels of compliance with percentage-expressed orders than fixed orders, holding the income of the custodial parent and the child support order constant, at least when both were subject to withholding. We have also used a structural model of child support compliance

TABLE 6.4

Estimates of Structural Compliance Model, with Exact Compliance Defined as *t/s* ε [.90, 1.10]

	Specification					
	I		*II*		*III*	*IV*
Parameter	*P*	*F*	*P*	*F*	*P*	*F*
Distribution of the Father's Cobb-Douglas Utility Parameter (δ_f)						
ψ_1	2.727 (1.335)	3.188 (0.503)	**2.967** **(0.447)**	0.683 (0.192)	3.199 (0.504)	**2.967** **(0.429)**
ψ_2	1.475 (1.012)	0.917 (0.191)	**0.923** **(0.187)**	2.460 (1.161)	0.926 (0.192)	**0.923** **(0.176)**
$E(\delta_f)$	0.649	0.777	0.763	0.217	0.775	0.763
$SD(\delta_f)$	0.209	0.184	0.192	0.203	0.184	0.192
Distribution of the Noncompliance Cost Parameter (ϑ)						
ψ_3	1.246 (1.028)	0.639 (0.193)	0.887 (0.608)	0.656 (0.199)	**1.232** **(0.808)**	**0.681** **(0.191)**
$E(\vartheta)$	0.803	1.565	1.127	1.524	0.812	1.468
$\mathfrak{L}$	-390.481		-392.465		-392.535	-392.536

Note: Restricted parameters are in boldface.

to investigate whether fathers with percentage-expressed orders differ from fathers with fixed orders in terms of their relative preferences for own versus child consumption and/or in terms of the distribution of costs of noncompliance. The inferences to be drawn from these results are more or less consistent with those obtained from the reduced-form estimates.

In the future we hope to develop the behavioral model so as to model the cost of noncompliance distribution in a more satisfactory manner. With larger samples, and using more information from the court records associated with these data, we would like to more specifically define costs of noncompliance (for example, in terms of court appearances and sanctions) so as to isolate the characteristics of percentage-expressed orders which make them more difficult to enforce than fixed orders.

APPENDIX A

Likelihood Function for the Four Groups of Fathers

C1: *No Transfer*

Only those fathers with preference parameter $\delta_f \geq y_f/y_t$ would make no transfer if it were not stipulated. Conditional on δ_f, $\delta_f \geq y_f/y_t$, and the characteristics *y* and *s*, the probability of noncompliance is given by

$$P(t = 0 \mid \delta_f, \delta_f \geq y_f/y_t, y, s) = P(\vartheta \leq D_0(\delta_f, y, s)) = G(D_0(\delta_f, y, s); \psi_G),$$

where ψ_G is a finite-dimensional parameter vector which completely characterizes the distribution function *G*, and where $D_0(\delta_f, y, s) \equiv \delta_f \{\ell n(y_f) - \ell n(y_f - s)\} + (1 - \delta_f) \{\ell n(y_m) - \ell n(y_m + s)\}$. With *H* denoting the distribution function of the preference parameter δ_f in the population of noncustodial fathers, and with ψ_H denoting the finite-dimensional parameter vector which completely characterizes *H*, the probability of zero payment for a father with characteristics (*y*,*s*) is

$$P(t = 0 \mid y, s, \psi_G, \psi_H) = \int_{y_f/y_t}^{1} G(D_0(\delta_f, y, s); \psi_G)\; dH(\delta_f; \psi_H).$$

This probability represents the contribution of a member of *C1* to the sample likelihood, which we will denote L_{C1}.

C2: *Partial Compliance*

The probability that such an individual will not comply with the order is given by $G(D_1(\delta_f, y, s); \psi_G)$, where $D_1(\delta_f,y,s) \equiv \delta_f\ \ell n(\delta_f) + (1-\delta_f)\ \ell n(1-\delta_f) + \ell n(y_m+y_f) - \delta_f\ \ell n(y_f-s) - (1-\delta_f)\ \ell n(y_m+s)$. For an individual who partially complies, we can impute the value of his preference parameter since we observe his transfer and the income distribution of the parents. Since

$$t = y_f - \delta_f y_t,$$

$$\Rightarrow \delta_f = (y_f - t)/y_t.$$

The probability density function for the transfer t among this group of fathers is then given by

$$\tilde{h}(t;y_t,\psi_H) = h((y_f-t)/y_t;\psi_H)\ \left|\ \partial\delta_f/\delta t\ \right| = h((y_f-t)/y_t;\psi_H)\ /\ y_t.$$

The contribution to the likelihood for an individual who partially complies is then

$$L_{C2} = G(D_1((y_f-t)/y_t,y,s);\psi_G)\ \tilde{h}((y_f-t)/y_t;y_t,\psi_H).$$

C3: *Exact Compliance*

It is necessary to distinguish between two distinct types (in terms of δ_f) of fathers belonging to this group. One subgroup consists of those who would not make a transfer if not ordered to do so; these fathers have values of the preference parameter in the interval $[y_f/y_t, 1]$. The other subgroup consists of fathers who would make positive transfers even if not required to do so, but for less than the amount s; these fathers have values of the preference parameter which lie in the interval $((y_f-s)/y_t, y_f/y_t)$. The probability that the first set of fathers exactly complies with the order is given by

$$P(t = s \mid \delta_f, \delta_f \in [y_f/y_t,1], y,s,\psi_G) = 1 - G(D_0(\delta_f,y,s);\psi_G),$$

while the probability that the second set of fathers exactly complies is given by

$$P(t = s \mid \delta_f, \delta_f \in ((y_f-s)/y_t, y_f/y_t), y,s,\psi_G) = 1 - G(D_1(\delta_f,y,s);\psi_G).$$

The unconditional probability of exact compliance, which is the likelihood contribution L_{C3}, is then

$$P(t = s \mid y,s,\psi_G,\psi_H) = \int_{y_f/y_t}^{1} \{1 - G(D_0(\delta_f, y,s);\psi_G)\}\; dH(\delta_f;\psi_H)$$

$$+ \int_{(y_f-s)/y_t}^{y_f/y_t} \{1 - G(D_1(\delta_f, y,s);\psi_G)\}\; dH(\delta_f;\psi_H).$$

C4: *Overcompliance*

The likelihood contribution for members of this group is simply $L_{C4} = \tilde{h}((t;y_t,\psi_H)$.

The likelihood function is then $\prod_{j=1}^{4} L_{Cj}$.

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