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Child disability, welfare payments, marital status and mothers' labor supply: Evidence from Australia

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Abstract: This paper studies the effects of child disability on mothers' participation in the labor force using Australian data. We formulate a bivariate Probit model in which mothers' employment and welfare recipient status are treated as the dependent variables and child disability is responsible for the both dependent variables. Several propositions concerning the impacts of child disability on Australian mothers' participation in the labor force are tested. Our testing procedure involves one-sided restrictions under the null or alternative hypotheses. Our main findings are as follows. A more severe child disability imposes greater restrictions on single mothers' participation in the labor force. Single mothers are less likely than mothers with a partner to participate in the labor force in the event of a child health shock. There is some evidence of the disincentive effect of welfare payments in encouraging mothers' participation in the labor force, particularly for single mothers.

Subjects: Multivariate Statistics; Employment & Unemployment; Econometrics

Keywords: child disability; extended MaxT test; female labor supply; one-sided test

1. Introduction

The relationship between child rearing and parental economic behavior has long attracted economists' attention. Child health is an important aspect of child rearing that has close bearings on parental economic behavior (see, e.g. Condliffe & Link, 2008; Currie, 2000, 2009). Because the mother in a household usually assumes the primary responsibility for the care of children, the impact of a child's disability on the mother's labor supply has been a subject of research over the past two decades or so (see surveys by, e.g. Frijters, Johnston, Shah, & Shields, 2009; Lu & Zuo, 2010; Powers, 2003).

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PUBLIC INTEREST STATEMENT

This paper examines the impacts of child disability on mothers' labor supply using the Australian survey data of the Survey of Disability, Ageing and Carers 2003 conducted by the Australian Bureau of Statistics. We also look at how welfare payment and mother's marital status relate to the impacts. Our main findings are as follows. A more severe child disability imposes greater restrictions on single mothers' participation in the labor force. Single mothers are less likely than mothers with a partner to participate in the labor force in the event of a child health shock. There is some evidence of the disincentive effect of welfare payments in encouraging mothers' participation in the labor force, particularly for single mothers.

Mothers in different family structures may react differently when they are presented with a disabled child. In single parent families the mother may struggle with the roles of primary care-giver and sole income earner. Mothers in dual parent families may be able to stay at home to look after their disabled child because of financial support from their partners, or they may be able to continue their work as their partners share in the care of the health-impaired child. Whether there exists a different impact of child disability on a single mother and a mother with a partner is of policy interest. If family structure plays an important role on the impacts of child disability on mothers' labor market activities, government policy could help provide better support to affected families by reflecting on family structure.

Government assistance, including financial support to affected families, is important for several reasons. For example, research has found that income has an impact on child health; children from poor families are more likely to experience a health problem or an exacerbation of a health problem than children from wealthy families (see, e.g. Case, Lubotsky, & Paxson, 2002; Condliffe & Link, 2008; Currie & Stabile, 2003). Also, the loss of income from paid work due to the presence of a disabled child could put the affected family at risk of persistent generational poverty (see, e.g. Currie, 2009; Powers, 2001, 2003). However, the public expenditure associated with welfare payments in many developed countries remains historically high (see, e.g. Klein, 2014). This inevitably puts pressure on a government's budget. Furthermore, the disincentive of welfare payments together with the alarming fact that more single mothers than mothers with a partner occupy the list of welfare recipients have increasingly attracted the attention of policy makers and economists (see, e.g. Moffitt, 1992). Such concerns have been an important driver of welfare reform in the modern era. In Australia the Federal Government introduced the Work for the Dole Act in 1997 for the first time in Australian history. This development raises important questions such as how mothers' labor market activities respond to child disability taking into account the influence of government welfare payments; whether a more severe child disability imposes more restrictions on the mother's labor supply; and to what extent, if any, does a differential effect of child disability exist between a single mother and a mother with a partner since they are likely to have different government welfare entitlements. This paper attempts to examine issues using Australian data.

The disincentive effect of welfare payments on the labor supply of mothers with a disabled child has been recognized by many authors (see, e.g. Corman, Noonan, & Reichman, 2005; Gould, 2004; Powers, 2001, 2003; Wolfe & Hill, 1995). Nevertheless, existing studies model the disincentive effect of welfare payments through the inclusion of a welfare variable as an exogenous regressor in single-equation models. In this paper we adopt bivariate probit (BiProbit) models which allow us to model the conditional effect of welfare payments on the labor supply of mothers with a disable child. Since its introduction by Heckman (1978) BiProbit models have been a popular choice in applied research (see, e.g. Bhattacharya, Goldman, & McCaffrey, 2006; Evans & Schwab, 1995; Goldman et al., 2001; Neal, 1997). Bhattacharya et al. (2006) show some evidence on the favorable performance of BiProbit models against some two-step estimators.

Past studies suggest that child disability can have negative impacts on mothers' labor supply (see, e.g. Breslau, Salkever, & Staruch, 1982; Corman et al., 2005; Frijters et al., 2009; Kimmel, 1997, 1998; Porterfield, 2002; Powers, 2001, 2003; Salkever, 1982; Zimmer, 2007). However, evidence concerning the differential effect of child disability between single mothers and mothers with a partner is inconclusive. Wolfe and Hill (1995) and Lu and Zuo (2010) argue that partnered mothers having a disabled child are more likely to participate in the labor force than single mothers, whereas Powers (2001, 2003) argues the opposite. Furthermore, the conclusions of existing studies are drawn from descriptive analysis. This paper adopts one-sided tests to rigorously gauge the evidence on the differential effect of child disability between single mothers and mothers with a partner (see, e.g. Andrews & Barwick, 2012; Andrews & Guggenberger, 2010; Bugni, 2010; Chernozhukov, Hong, & Tamer, 2007; Hansen, Lunde, & Nason, 2011; Lee, Song, & Whang, 2013; Linton, Song, & Whang, 2010; Lu, 2016; Romano, Shaikh, &

Wolf, 2014; Rosen, 2008 for the recent literature on one-sided tests). We also test the impact of welfare payments on the labor supply of mothers of disabled children, and how the severity of child disability restricts the mothers' labor supply. The one-sided hypothesis test approach allows us to examine the directional empirical evidence against the sampling error. Our main findings are:

(1) A more severe child disability imposes greater restrictions on single mothers' participation in the labor force.

(2) Single mothers are less likely than mothers with a partner to participate in the labor force in the event of a child health shock.

(3) There is some evidence of the disincentive effect of welfare payments in encouraging mothers' participation in the labor force, particularly for single mothers.

The remainder of the paper is organized as follows. The next section presents the econometric techniques used in our empirical studies. It includes the construction of models and applications of one-sided hypothesis tests. Section 3 describes the data we use. Section 4 carries out the empirical studies and discusses the findings. Some concluding remarks are made in Section 5.

2. Econometric analysis

2.1. The models

Denote by y_1 the variable for an individual mother's labor supply and by y_2 her status of being a recipient of a government welfare payment. y_1 and y_2 are endogenously determined. Let x be a column vector of exogenous variables that include the child disability variable D and are responsible for both mother's labor supply and the status of receiving a government welfare payment. Let w be a column vector of exogenous variables that are only responsible for mothers' labor supply. We are interested in estimating the marginal effect of D on y_1. This effect comes from two sources. One is the direct effect of D on y_1 and the other is the indirect effect of D on y_1 through y_2. Complications arise from the identification of the composite effect together with the discrete nature of y_1 and y_2. In this paper we adopt a parametric approach in which the combined direct and indirect effects of child disability on a mother's labor supply are estimated. Our parametric specification allows our estimation to rely only on the identification of reduced form (RF) parameter not on the identification of structural parameter as that usually requires valid instruments (see, e.g. Millimet & Tchernis, 2013). That is, we can only estimate the combined direct and indirect effects, but we cannot separate them.

Let the subscript i index the ith observation (mother) from an independent and identically distributed sample of n mothers. Denote y_{1i}^* and y_{2i}^* the latent counterparts of y_{1i} and y_{2i}, respectively. We assume the model of the structural form (SF) as

$$y_{1i}^* = \gamma_1 y_{2i}^* + \beta_1' x_i + \beta_2' w_i + u_1, \tag{2.1a}$$

$$y_{2i}^* = \gamma_2 y_{1i}^* + \alpha_1' x_i + u_2, \tag{2.1b}$$

where the error term $(u_1,\ u_2)'$ follows the bivariate normal distribution with the zero mean and the covariance matrix

$$\Sigma = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix},$$

$-1 < \rho < 1, \sigma_1 > 0$ and $\sigma_2 > 0$. The RF of the SF Equations (2.1) is

$$y_{1i}^* = \pi_1' v_{1i} + \varepsilon_1, \tag{2.2}$$

$$y_{2i}^* = \pi_2' v_{2i} + \varepsilon_2, \tag{2.3}$$

where the error term $(\varepsilon_1, \varepsilon_2)'$ is the bivariate normal random variable with the zero mean and covariance matrix of

$$\Omega = \begin{pmatrix} 1 & \tau \\ \tau & 1 \end{pmatrix},$$

where $-1 < \tau < 1$. Note that x_i that includes child disability variable D_i are part of v_{1i} and v_{2i}.

For the mothers' employment status variable, y_{1i}, and the welfare status variable, y_{2i}, we define $y^*_{ki} > 0$ for participating in the labor force ($k = 1$) or receiving a welfare payment ($k = 2$) and observe

$$y_{ki} = 1 \qquad \text{if} y^*_{ki} > 0, \tag{2.4}$$

$$y_{ki} = 0 \qquad \text{otherwise}, \tag{2.5}$$

$k = 1, 2$. For presentation convenience we may let $s_{ki} = 2y_{ki} - 1$. The log-likelihood function of the RF model is

$$l_P(\theta) = \sum_{i=1}^{n} \log \Phi_2(s_{1i}\pi_1' v_{1i}, s_{2i}\pi_2' v_{2i}; s_{1i}s_{2i}\tau), \tag{2.6}$$

where $\theta = (\pi_1', \ \pi_2', \ \tau)'$ and $\Phi_2(\cdot, \cdot; \tau)$ is the cumulative distribution function of the bivariate standard normal random variable with the correlation τ.

The effects of the child disability variables on the labor supply can be identified based on the RF parameter. They, hence, avoid the potential identification problem of the SF parameter. For BiProbit models the probability of the ith mother participating in the labor force conditional on the status of receiving a welfare payment (s_2 or y_2) is

$$m_i(s_{2i}; \theta) = \frac{\Phi_2(\pi_1' v_{1i}, s_{2i}\pi_2' v_{2i}; s_{2i}\tau)}{\Phi(s_{2i}\pi_2' v_{2i})}.$$

Because our child disability variables are more than one dummy variable, with the value 1 indicating the child disability being in a particular category of severity, the effect of a particular child disability variable, D_q, $q = 1, \dots Q$, on m_i is defined as

$$\Delta m_{i,q}(s_{2i}; \theta) = m_i(s_{2i}; \theta)|_{D_q=1} - m_i(s_{2i}; \theta)|_{D_q=0}, \tag{2.7}$$

and the average effect is estimated as

$$\Delta \hat{m}_q(s_2) = n^{-1} \sum_{i=1}^{n} \Delta m_{i,q}(s_{2i}; \hat{\theta}). \tag{2.8}$$

As all the conditional effects m are highly nonlinear functions of θ, we estimate the covariance of $\Delta\hat{m}$ through a bootstrap procedure in which we randomly draw a number of samples of size n with replacements from the original sample and estimate $\Delta\hat{m}_q$, $q = 1, \dots Q$, according to (2.8) for each random sample.

2.2. Tests of directional effects

Suppose we wish to examine whether child disability decreases the probability of work by single mothers more than that for mothers with a partner conditional on the status of receiving a welfare payment. That is, to test $h_q = \Delta_p m_q(s_2) - \Delta_s m_q(s_2) \geq 0$, $q = 1, \dots, Q$, where $\Delta m_q(s_2) = \lim_{n\to\infty} E\Delta\hat{m}_q(s_2)$, the subscripts p and s at the left-hand side m denote mothers with a partner and single mothers, respectively. Two-sided tests do not take into account the nature of one-sided restrictions. Consequently, their powers may be compromised. Therefore, it is more appropriate to carry out one-sided tests of directional effects. There are different formulations of one-sided hypotheses under different assumptions. For example, the researcher may be willing to assume the impact of child disability on the probability to work for partnered mothers cannot be more negative than that for single mothers and seek evidence on whether child disability decreases the probability to work for single mothers more than that for mothers with a partner. Then we could adopt EMaxT tests of Lu (2016) for simultaneously testing of the multiple hypotheses,

$$H_q{:}h_q = 0 \quad \text{vs.} \quad H_q^a{:}h_q > 0, \quad q \in \mathbf{Q} = \{1, \ldots, Q\}, \tag{2.9}$$

and the global hypotheses

$$H_{\mathbf{Q}}{:} \cap_{\forall q} H_q \quad \text{vs.} \quad H_{\mathbf{Q}}^a{:} \cup_{\forall q} \{h_q \geq 0\} - \cap_{\forall q} H_q, \tag{2.10}$$

with the control of the familywise error rate (FWE) for the multiple hypothesis tests (see, e.g. Romano & Wolf, 2005a, 2005b; Romano, Shaikh, & Wolf, 2010 for discussions of multiple tests). EMaxT tests are motivated for improving the global power of existing MaxT tests at some (sometime little) cost of the multiple testing power. EMaxT tests have been shown that they can have considerable global power improvement over MaxT tests, and are more robust against the normality assumption than likelihood ratio (LR) tests in global testing.

Let $h = (h_1, \ldots, h_Q)'$. Assume

$$n^{\frac{1}{2}} \hat{\Sigma}^{-\frac{1}{2}} \left(\hat{h} - h\right) \xrightarrow{d} N(0, I),$$

where $\hat{\Sigma}$ is a consistent estimate of Σ, $\hat{\Sigma}^{1/2}$ is the matrix such that $\hat{\Sigma}^{1/2}\hat{\Sigma}^{1/2} = \hat{\Sigma}$, I is the identity matrix and $\xrightarrow{d}$ denotes the convergence in distribution. We further assume that $\hat{h}$ is studentized and $\hat{\Sigma}$ is the estimated correlation matrix (see Romano & Wolf, 2005b for rationales of studentization for constructing MaxT tests). EMaxT tests have the test statistic as

$$T_E = \max(n^{\frac{1}{2}} \hat{b}' \hat{\Sigma}^{-1} \hat{h}, n^{\frac{1}{2}} \hat{h}_1, \ldots, n^{\frac{1}{2}} \hat{h}_Q),$$

where $\hat{b} \in \{\hat{b} \in R^Q{:}\hat{b}'\hat{\Sigma}^{-1}\hat{b} = 1\}$ is computed by Algorithm 1 in Lu (2016) using $\hat{\Sigma}$. Denote by $c_{\alpha,E}$ the critical value such that $\Pr_{h=0}(T_E > c_{\alpha,E}) = \alpha$. In global testing $H_{\mathbf{Q}}$ is rejected if $T_E > c_{\alpha,E}$. In multiple testing H_q, $q \in \mathbf{Q}$, is rejected if $n^{\frac{1}{2}} \hat{h}_q > c_{\alpha,E}$. $c_{\alpha,E}$ or p -value can be approximated by the Monte Carlo procedure stated in Algorithm 2 of Lu (2016) or analytically computed by Equation (12) of Lu (2016) in the case of $Q = 2$.

For a robustness check on testing results we also consider conventional MaxT tests, LR tests and the one-sided Wald tests of Andrews (1998). MaxT tests are implemented with the test statistic

$$T_M = \max(n^{\frac{1}{2}} \hat{h}_1, \ldots, n^{\frac{1}{2}} \hat{h}_Q).$$

Denote by $c_{\alpha,M}$ the critical value such that $\Pr_{h=0}(T_M > c_{\alpha,M}) = \alpha$. In the global testing $H_{\mathbf{Q}}$ is rejected if $T_M > c_{\alpha,M}$. In multiple testing H_q, $q \in \mathbf{Q}$, is rejected if $n^{\frac{1}{2}} \hat{h}_q > c_{\alpha,M}$. Note that generally the use of $c_{\alpha,M}$ computed under $h = 0$ leads to the weak control of FWE (see, e.g. Dudoit, Shaffer, & Boldrick, 2003; Romano & Wolf, 2005a). The strong control of FWE demands the control of FWE under any combination of true and false null hypotheses, i.e. $h_q = 0$, $q \in \mathbf{r}$, $\forall \mathbf{r} \subseteq \mathbf{Q}$. If one is willing to assume that the distribution of individual p-values for testing H_q is uniformly distributed on (0, 1) under $h_q = 0$, then following Romano and Wolf (2005a) MaxT tests using $c_{\alpha,M}$ ensure the strong control of FWE in the individual test of H_q, $q \in \mathbf{Q}$. Because $c_{\alpha,E} > c_{\alpha,M}$ as shown in Lu (2016) it follows that our EMaxT tests also have the strong control of FWE in individual hypothesis testing.

LR tests are implemented with the test statistic (see, e.g. Wolak, 1989a, 1989b),

$$T_{L1} = n\{\hat{h}'\hat{\Sigma}^{-1}\hat{h} - \inf_{h\geq 0}(\hat{h}-h)'\hat{\Sigma}^{-1}(\hat{h}-h)\}. \tag{2.11}$$

The limiting null distribution of T_{L1} is the so-called chi-bar-square ($\overline{\chi}^2$) distribution, which is a mixture of chi-square random variables as $\overline{\chi}^2 = \sum_{j=0}^{Q}\omega(Q,j,\Sigma)\chi_j^2$, where χ_0^2 has a mass of 1 at 0 and $\omega(Q,j,\Sigma)$ is the mixing probability of having j positive elements out of Q in the solution to the quadratic programming problem in (2.11) (see, e.g. Wolak, 1987). The p-value can be computed as

$$p\text{-value} = \sum_{j=1}^{Q}\omega(Q,j,\hat{\Sigma})\Pr(\chi_j^2 > T_{L1}).$$

The one-sided Wald tests of Andrews (1998) are implemented with the test statistic

$$D\text{-}W_{\infty} = n\{\hat{h}'\hat{\Sigma}^{-1}\hat{h} + 2\log\Phi(B,\hat{h},\hat{\Sigma})\},$$

where $\Phi(B,h,\Sigma) = \Pr(U\in B), U\sim N(h,\Sigma)$ and $B=\{h\geq 0\}$. We follow Andrews' suggestion of simulating the null distribution by $U_0'U_0 + 2\log\Phi(B,\hat{\Sigma}^{1/2}U_0,\hat{\Sigma})$, where $U_0 \sim N(0,I)$.

The hypothesis settings (2.9) and (2.10) become inappropriate if the assumption that $h\leq 0$ cannot occur is violated. For example, the researcher may argue that child disability of some degrees of severity has higher negative impacts on single mothers than mothers with a partner, while child disability of other degrees of severity has lower negative impacts on single mothers than mothers with a partner. If one cannot assume a priori knowledge of that it can only be possible that $h\geq 0$, then the hypotheses (2.9) and (2.10) should be re-formulated as

$$H_q^I{:}h_q < 0 \quad \text{vs.} \quad H_q^{I,a}{:}h_q > 0, \quad q\in\mathbf{Q}, \tag{2.12}$$

and

$$H_{\mathbf{Q}}^I{:}h\leq 0 \quad \text{vs.} \quad H_{\mathbf{Q}}^I \text{ is not true}, \tag{2.13}$$

respectively. In this paper we extend EMaxT tests for testing H_q^I and $H_{\mathbf{Q}}^I$ as follows.

Let Q^* be the number of non-negative elements in h_0 and Σ_{Q^*} is the covariance of associated estimate. Q^* can be consistently estimated by the dimension of $\hat{h}^* = (h_1,\dots,h_{Q^*})' = \{\hat{h}_q{:}\hat{h}_q \geq -(b_n/n)^{-1/2}, q=1,\dots,Q\}$, where b_n is a sequence satisfying

$$b_n\to\infty, b_n/n\to 0. \tag{2.14}$$

Choices of b_n that satisfy (2.14) have been suggested by several authors (e.g. Andrews, 1999; Andrews & Soares, 2010; Donald & Hsu, 2011; Hansen, 2005; Rosen, 2008). For example, $b_n = \log n$ in Andrews and Soares (2010) and $b_n = \log\log n$ in Hansen (2005). Let $\hat{\Sigma}^*$ be the correlation matrix corresponding to $\hat{h}^*$. Then implement EMaxT tests by using $\hat{h}^*$ and $\hat{\Sigma}^*$. MaxT tests are implemented similarly. LR tests are implemented with the test statistic,

$$T_{L2} = n\inf_{h\geq 0}(-\hat{h}-h)'\hat{\Sigma}^{-1}(-\hat{h}-h), \tag{2.15}$$

that has the limiting null distribution $\overline{\chi}^2(Q^*) = \sum_{j=0}^{Q^*}\omega(Q^*,Q^*-j,\Sigma_{Q^*})\chi_j^2$.

Some authors find that the choice of b_n can have an influential role in the performance of one-sided tests (e.g. Donald & Hsu, 2011). In fact, we can show that there always exists a b_n that satisfies the condition (2.14) such that any $Q^* \in \{1, \ldots, Q\}$ can be an estimate for a given sample of size n. Consider $b_n = (\log n)^a$, $a > 0$, which can be verified satisfying the condition (2.14). Because b_n is a monotonically increasing function of a when $n \geq 3$, the dimension of Q^* is likely to increase as a increases. This effectively implies that given n any $Q^* \in \{1, \ldots, Q\}$ can be an estimate by choosing an appropriate a. Therefore, it is important to check the sensitivity of test results to the estimate Q^*. We suggest that tests be performed as follows. Order the elements of $\hat{h}$ such that the first element is the smallest. Let $\hat{h} = (\hat{h}_1', \hat{h}_2')'$, where $\hat{h}_1 < 0$, $\hat{h}_2 \geq 0$ and $\hat{Q}_0^*$ be the dimension of $\hat{h}_2$. Then perform tests at $\hat{Q}^* = Q, Q-1, \ldots, \hat{Q}_0^*$. The p-value can be computed as

$$p\text{-value} = \sum_{j=0}^{\hat{Q}^*} \omega(\hat{Q}^*, \hat{Q}^* - j, \hat{\Sigma}_{Q^*}) \Pr(\chi_j^2 > T_{L2}).$$

3. Data and descriptive analysis

The data used in this paper are extracted from the Survey of Disability, Ageing and Carers 2003, which was the fifth comprehensive national survey conducted by the Australian Bureau of Statistics (ABS) to collect information on people with a disability, older people and people who care for persons with a disability and older people. In the survey, people were identified as having a disability if they had one or more of the listed limitations, restrictions or impairments which had lasted, or was likely to last, for a period of six months or more and restricted everyday activities. The list is provided in Appendix 1.

Four categories of disability status are first constructed according to the ABS definitions: profoundly, severely, moderately/mildly limited and not limited in core activities. Core activities include self care, mobility and communication.[1] The definitions for these categories of child disability are provided in Appendix 1.

There are 41,233 individuals with household, family and person identifiers in the survey. Of these, 3,934 females aged from 25 to 64 years have at least one child in the household. Forty-nine of these females are excluded in our analysis as they indicate that their main reason for not looking for work is that they do not need or want to work.[2] Fifty-eight females, including adult children, are omitted so that all of the females in our sample are either a wife/partner (including same-sex partner) in the household or a lone parent. This reduces the number of mothers to 3,827. Ten mothers with a profound disability of their own are dropped from the sample because they are not in the labor force. As only one of the nine single mothers with a profound own disability is in the labor force, we exclude these nine single mothers from the sample. The final sample consists of 3,808 mothers, of whom 2,800 have a partner[3] and 1,008 are single mothers. We also study the labor market activities of mothers who do not have an own disability. There are 3,332 mothers without their own disability, of whom 2,511 are mothers with a partner and 821 are single mothers.

The ABS data are collected in a way that each observation is attached to a population weight. Table 1 provides the descriptive statistics for both weighted and unweighted samples for the mothers, including those with an own disability, while Table 2 provides these for the mothers, excluding those with an own disability. It shows that the results for weighted and unweighted samples are slightly different. Further analysis is conducted using the weighted sample.

Table 3 displays the labor force participation rates of mothers with disabled children under the different levels of disability severity for the mothers, including or excluding those having an own disability, respectively. The tables also include information on mothers with able children. They reveal some prima facie evidence on the relationship between child disability, welfare payments,[4] marital

Table 1. Sample information with standard deviation in parenthesis for mothers, including those having an own disability

Variable	Definition	Sample proportion/mean	
		weighted	unweighted
Employment	1 if in labor force, 0 otherwise	0.663	0.671
Hourswk	Hours worked per week	25.562 (14.201)	25.453 (14.148)
Welfare	1 if the mother receives a welfare payment, 0 otherwise	0.323	0.334
ChildDisis1	1 if the child disability is profoundly limited in core activities, 0 otherwise	0.033	0.034
ChildDisis2	1 if the child disability is severely limited in core activities, 0 otherwise	0.037	0.036
ChildDisis3	1 if the child disability is moderately/mildly limited in core activities, 0 otherwise	0.022	0.021
ChildDisis4	1 if the child disability is not limited in core activities, 0 otherwise	0.038	0.040
Age	Age of the observation minus 45	−7.770 (6.567)	−7.513 (6.476)
Degree	1 if the highest education is degree or above, 0 otherwise	0.221	0.219
Diploma	1 if the highest education is certificate, diploma or advanced diploma, 0 otherwise	0.289	0.280
Year12	1 if the highest education is year 12, 0 otherwise	0.164	0.164
IncomeMis	1 if income gap (unit income minus personal income) is not available, 0 otherwise	0.196	0.188
LnIncome	Natural log of income that is unit income minus	4.534	4.558
	Personal income and is set as 0 if it is missing	2.878	2.856
Ykidage	Age of the youngest dependent child	6.100 (4.268)	6.238 (4.268)
NoChildren	Number of children under 15 in the family	1.869 (0.857)	1.866 (0.859)
OwnDis1	1 if own disability is severely limited in core activities, 0 otherwise	0.022	0.025
OwnDis2	1 if own disability is moderately/mildly limited in core activities, 0 otherwise	0.049	0.053
OwnDis3	1 if own disability is not limited in core activities, 0 otherwise	0.046	0.047
NoPersonWel	Number of persons in the household other than mother and partner receiving welfare payments	0.112 (0.421)	0.112 (0.426)

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Table 2. Sample information with standard deviation in parenthesis for mothers, excluding those having an own disability

Variable	Definition	Sample proportion/mean	
		weighted	unweighted
Employment	1 if in labor force, 0 otherwise	0.679	0.688
Hourswk	Hours worked per week	25.658 (14.069)	25.544 (14.015)
Welfare	1 if the observation receives any government welfare benefit payment, 0 otherwise	0.303	0.313
ChildDisis1	1 if the child disability is profoundly limited in core activities, 0 otherwise	0.028	0.029
ChildDisis2	1 if the child disability is severely limited in core activities, 0 otherwise	0.029	0.029
ChildDisis3	1 if the child disability is moderately/mildly limited in core activities, 0 otherwise	0.020	0.019
ChildDisis4	1 if the child disability is not limited in core activities, 0 otherwise	0.033	0.034
Age	Age of the observation minus 45	−7.903 (6.516)	−7.629 (6.430)
Degree	1 if the highest education is degree or above, 0 otherwise	0.226	0.226
Diploma	1 if the highest education is certificate, diploma or advanced diploma, 0 otherwise	0.285	0.276
Year12	1 if the highest education is year 12, 0 otherwise	0.170	0.170
IncomeMis	1 if income gap (unit income minus personal income) is not available, 0 otherwise	0.197	0.191
LnIncome	Natural log of income that is unit income minus personal income and is set as 0 if it is missing	4.590 (2.878)	4.608 (2.863)
Ykidage	Age of the youngest dependent child	5.959	6.109
		−4.250	−4.256
NoChildren	Number of children under 15 in the family	1.878 (0.854)	1.875 (0.852)
NoPersonWel	Number of persons in the household other than mother and partner receiving welfare payments	0.101 (0.409)	0.101 (0.413)

status and mothers' labor market activity. It appears that for mothers of profoundly or severely disabled children (ChildDis1 and ChildDis2) their labor force participation rates are lower than for mothers with able children and they become even lower as the severity of child disability worsens except for mothers with a partner who have an own disability and receive welfare. The evidence is less clear for mothers of disabled children who do not have a profound or severe limitation (ChildDis3 and ChildDis4). For mothers with a partner who do not receive welfare and have a disabled child whose disability is not limited in core activities (ChildDis4), their labor force participation rate is even greater than that of mothers of able children. Comparing mothers with a partner with single mothers shows

Table 3. Employment for mothers including and excluding those having an own disability

	ChildDis1	ChildDis2	ChildDis3	ChildDis4	able children
Mothers including those having an own disability					
Mothers with a partner receiving welfare					
In labor force	31	17	9	17	243
Not in labor force	39	23	12	10	265
Participation rate	44	43	42	62	48
Mothers with a partner not receiving welfare					
In labor force	10	32	21	51	1488
Not in labor force	8	14	9	15	487
Participation rate	57	70	71	77	75
Single mothers receiving welfare					
In labor force	8	12	13	15	248
Not in labor force	23	28	11	20	230
Participation rate	27	30	54	43	52
Single mothers not receiving welfare					
In labor force	5	9	6	11	266
Not in labor force	6	6	4	4	82
Participation rate	44	59	62	72	76
Mothers excluding those having an own disability					
Mothers with a partner receiving welfare					
In labor force	23	12	6	16	216
Not in labor force	29	17	10	6	232
Participation rate	44	41	39	72	48
Mothers with a partner not receiving welfare					
In labor force	9	22	19	46	1376
Not in labor force	4	13	7	8	441
Participation rate	66	63	74	85	76
Single mothers receiving welfare					
In labor force	5	10	9	12	207
Not in labor force	19	15	8	13	182
Participation rate	20	41	55	46	53
Single mothers not receiving welfare					
In labor force	4	8	5	9	242
Not in labor force	3	3	3	2	65
Participation rate	52	73	63	81	79

that child disability has higher negative impacts on single mothers than mothers with a partner. Looking across the status of welfare payments for single mothers and mothers with a partner, the tables reveal that mothers are less likely to participate in the labor force if they receive welfare payments. This is true regardless of whether their children have a disability or not. However, such a disincentive effect appears to dampen as the severity of child disability worsens; the difference in labor force participation rates between those receiving and those not receiving a welfare payment decreases as the severity of child disability worsens.

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4. The results of estimation and testing

Our BiProbit estimates take into account the population weights of sample observations. Our weighted BiProbit estimates are obtained by adjusting the log-likelihood functions as $l_w(\theta) = \sum_{i=1}^{n} w_i l_i(\theta)$, where w_i is the weight associated with the ith observation, $\sum_{i=1}^{n} w_i = n$ and $l_i(\theta)$ the log-likelihood function for the ith observation, which is the summand in Equation (2.6). The average treatment effect such as in Equation (2.8) is adjusted by the weighted sample average, for example, $\Delta\hat{m}_q = n^{-1} \sum_i^n w_i \Delta m_{i,q}(\hat{\theta})$. The random draws in the bootstrap procedure are implemented according to the sample weight.

Tables 4 and 5 report the estimated RF models of BiProbit models for the group of mothers having or not having an own disability. The reported standard errors of estimates are obtained through the bootstrap procedure in which 1000 samples through random sampling with replacement are used. Note that we initially estimated models with the child disability variables ChildDis3 and ChildDis4 as two separate variables, but found their associated coefficient estimates are highly insignificant. The reported results are based on amalgamating ChildDis3 and ChildDis4 (denoted as ChildDis34). The estimated correlation coefficients τ are significant suggesting a correlation of mothers' employment and the welfare variable. The sign of estimate of coefficients associated with the child disability (ChildDis1, ChildDis2 and ChildDis34) confirms that child disability has a negative effect on mothers' labor supply, but a positive effect on the probability of their being a welfare payment recipient. Note that the sign of estimate of coefficients associated with severe child disability (ChildDis2) on single mothers' welfare payment is negative, but insignificant.

Table 4. Estimates of the RF of BiProbit models for mothers, including those having an own disability

	Mothers with a partner				Single mothers			
	Work decision		Welfare		Work decision		Welfare	
	Coeff.	Std. err	Coeff.	Std. err	Coeff.	Std. err	Coeff.	Std. err
Constant	−0.01	0.21	−0.14	0.21	−0.50	0.24	1.29	0.25
ChildDis1	−0.46	0.15	1.52	0.17	−0.63	0.25	0.32	0.25
ChildDis2	−0.22	0.18	0.65	0.16	−0.43	0.23	0.02	0.22
ChildDis34	−0.07	0.12	0.34	0.13	−0.13	0.18	0.20	0.18
Age	−0.04	0.01	0.00	0.01	−0.02	0.02	−0.02	0.02
Age-square	-3×10^{-3}	1×10^{-3}	2×10^{-4}	5×10^{-4}	-5×10^{-4}	9×10^{-4}	-2×10^{-3}	9×10^{-4}
Degree	0.58	0.09	−0.57	0.09	1.06	0.16	−0.74	0.15
Diploma	0.41	0.07	−0.09	0.08	0.46	0.11	−0.13	0.11
Year12	0.26	0.08	−0.11	0.09	0.29	0.14	−0.29	0.14
IncomeMis	−0.40	0.19	−0.63	0.17	−0.18	0.16	−1.40	0.17
LnIncome	0.02	0.03	−0.09	0.02	0.04	0.02	−0.23	0.03
YChildAge	0.11	0.01	−0.05	0.01	0.10	0.02	−0.03	0.01
No. Children	−0.18	0.03	0.13	0.04	−0.13	0.06	0.13	0.06
No. PersonWel	−0.41	0.07	0.24	0.08	−0.31	0.11	0.08	0.10
OwnDis1	−0.72	0.22	0.59	0.18	−1.17	0.43	−0.01	0.29
OwnDis2	−0.64	0.16	0.20	0.16	−0.64	0.19	0.56	0.19
OwnDis3	0.23	0.15	0.15	0.15	−0.14	0.19	0.04	0.20
τ	−0.32	0.04			−0.34	0.06		
Log-likelihood	−2781.139				−1112.869			

Table 5. Estimates of the RF of BiProbit models for mothers, excluding those having an own disability

	Mothers with a partner				Single mothers			
	Work decision		Welfare		Work decision		Welfare	
	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.	Coeff.	Std. err.
Constant	−0.02	0.05	−0.17	0.04	−0.67	0.07	1.03	0.08
ChildDisis1	−0.53	0.03	1.64	0.05	−0.92	0.09	0.58	0.07
ChildDisis2	−0.40	0.03	0.66	0.03	−0.23	0.08	−0.07	0.08
ChildDisis34	0.05	0.02	0.37	0.02	−0.17	0.04	0.26	0.05
Age	−0.05	1×10^{-4}	3×10^{-3}	1×10^{-4}	−0.03	4×10^{-4}	−0.04	3×10^{-4}
Agesquare	0.00	0.00	0.00	0.00	0.00	0.00	1×10^{-4}	1×10^{-6}
Degree	0.54	0.01	−0.54	0.01	1.14	0.03	−0.76	0.02
Diploma	0.38	0.01	−0.08	0.01	0.49	0.02	−0.18	0.02
Year12	0.24	0.01	−0.07	0.01	0.21	0.02	−0.37	0.03
IncomeMis	−0.41	0.03	−0.55	0.03	−0.09	0.03	−1.60	0.04
LnIncome	0.02	0.00	−0.09	0.00	0.06	0.00	−0.24	0.00
YChildAge	0.12	0.00	−0.05	0.00	0.12	0.00	−0.03	0.00
No. Children	−0.19	0.00	0.13	0.00	−0.18	0.00	0.20	0.00
No. PersonWel	−0.41	0.01	0.22	0.01	−0.27	0.01	0.29	0.01
tau	−0.33	0.00			−0.37	0.00		
Log-likelihood	−2470.694				−891.759			

Examining the effects of other variables, whether income information is missing (IncomeMis) is found to be non-trivial in accounting for mothers' labor supply and their status of receiving a welfare payment. Mothers who do not provide their income information are less likely to participate in the labor force, as well as being less likely to receive government welfare payments. The evidence appears to be stronger for mothers with a partner than for single mothers. For those who do report family income information the income effects are positive on mothers' labor supply, but negative on mothers receiving welfare across all groups of mothers.[5] In relation to education attainment it appears that the better educated mothers are more likely to work and they are less likely to be welfare recipients. Signs of the estimates of the coefficients associated with other child variables (YChildAge and No.Children) are generally as expected; as the age of the youngest child increases or the number of children decreases the mother is more likely to work while they are less likely to receive government welfare payments. Mother's age appears to be trivial in determining their labor supply and their status of receiving welfare payments.[6] Other control variables such as location of mother and age of child are not found to be significant and so are not reported here.

Table 6 reports the estimated marginal effects of child disability on the probability of working (Δm) conditional upon receiving a government welfare payment or not (s_2). The results show that single mothers are less likely to work if they have a disabled child and work even less if the severity of child disability increases regardless of whether they receive a government welfare payment or not. However, this may not be true for mothers with a partner. Partnered mothers may work even more if they have a moderately/mildly or non-core activity limited disabled child (ChildDis34) as observed in the descriptive statistics analysis. To gauge evidence on this observation, we carry out hypothesis testing. Let $q = 1, 2, 3$ correspond to ChildDis1, ChildDis2 and ChildDis34, respectively, and the hypotheses be

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Table 6. Estimated marginal effects of child disability on the probability to work with the variance and covariance in parenthesis

	ChildDis1 (Σ_{11})	ChildDis2 (Σ_{22})	ChildDis34 (Σ_{33})	$\begin{pmatrix} \Sigma_{12} & \Sigma_{13} \\ & \Sigma_{23} \end{pmatrix}$
Mothers including those having an own disability				
Mothers with a partner				
Conditional on receiving welfare	−0.0521 (0.0028)	−0.0254 (0.0030)	0.0024 (0.0018)	$\begin{pmatrix} 0.0002 & 0.0002 \\ & 0.0001 \end{pmatrix}$
Conditional on not receiving welfare	−0.0454 (0.0024)	−0.0317 (0.0024)	−0.0049 (0.0013)	$\begin{pmatrix} 0.0002 & 0.0001 \\ & 0.0001 \end{pmatrix}$
Single mothers				
Conditional on receiving welfare	−0.1859 (0.0051)	−0.1386 (0.0043)	−0.0288 (0.0028)	$\begin{pmatrix} 0.0002 & 0.0003 \\ & 0.0004 \end{pmatrix}$
Conditional on not receiving welfare	−0.1737 (0.0064)	−0.1298 (0.0045)	−0.0219 (0.0021)	$\begin{pmatrix} 0.0003 & 0.0003 \\ & 0.0004 \end{pmatrix}$
Mothers excluding those having an own disability				
Mothers with a partner				
Conditional on receiving welfare	−0.0749 (0.0036)	−0.0859 (0.0036)	0.0540 (0.0022)	$\begin{pmatrix} 0.0003 & 0.0003 \\ & 0.0001 \end{pmatrix}$
Conditional on not receiving welfare	−0.0615 (0.0033)	−0.0866 (0.0033)	0.0352 (0.0014)	$\begin{pmatrix} 0.0002 & 0.0002 \\ & 0.0001 \end{pmatrix}$
Single mothers				
Conditional on receiving welfare	−0.2627 (0.0059)	−0.0764 (0.0071)	−0.0394 (0.0034)	$\begin{pmatrix} 0.0002 & 0.0003 \\ & 0.0004 \end{pmatrix}$
Conditional on not receiving welfare	−0.2444 (0.0089)	−0.0664 (0.0057)	−0.0282 (0.0025)	$\begin{pmatrix} 0.0002 & 0.0003 \\ & 0.0003 \end{pmatrix}$

$$H_0: \quad \Delta m_1 = \Delta m_2 = \Delta m_3$$
$$H_Q: \quad \Delta m_1 \le \Delta m_2 \le \Delta m_3 \le 0$$

and

$$H_0: \quad \Delta m_1 \ge \Delta m_2 \ge \Delta m_3 \ge 0$$
$$H_Q: \quad \Delta m_q \in R, q = 1, 2, 3.$$

with at least one inequality holding under H_Q. Apply the transformation $h = R\Delta m$, where $\Delta m = (\Delta m_1, \Delta m_2, \Delta m_3)'$ and

$$R = \begin{pmatrix} -1 & 1 & 0 \\ 0 & -1 & 1 \\ 0 & 0 & -1 \end{pmatrix},$$

Table 7. *p*-values of testing hypotheses (2.9) and (2.10) for mothers including those having an own disability

Testing $H_q{:}h_q = 0$ or $H_Q{:}\cap_{\forall q} H_q$									
EMaxT				**MaxT**			**LR**	***D-W***$_\infty$	**Wald**
H_e	H_1	H_2	H_3	H_1	H_2	H_3	H_Q	H_Q	H_Q
Proposition: More severe child disability has higher negative impacts on mothers' employment									
Mothers with a partner conditional on receiving welfare									
0.508	0.856	0.834	0.980	0.849	0.824	0.980	0.277	0.180	0.767
Mothers with a partner conditional on not receiving welfare									
0.471	0.917	0.814	0.938	0.915	0.802	0.938	0.274	0.168	0.756
Single mothers conditional on receiving welfare									
0.004	0.787	0.277	0.760	0.772	0.238	0.742	0.002	0.001	0.013
Single mothers conditional on not receiving welfare									
0.016	0.812	0.269	0.791	0.804	0.234	0.780	0.008	0.004	0.045
Proposition: Child disability has higher negative impacts on single mothers than mothers with a partner									
Conditional on receiving welfare									
0.435	0.192	0.257	0.669	0.182	0.247	0.667	0.115	0.068	0.278
Conditional on not receiving welfare									
0.187	0.242	0.319	0.748	0.231	0.310	0.748	0.167	0.100	0.380
Proposition: Child disability has higher negative impacts on mothers receiving welfare than mothers not receiving welfare									
Mothers with a partner									
0.974	0.454	0.994	0.994	0.449	0.994	0.994	0.461	0.682	0.403
Single mothers									
0.123	0.438	0.229	0.459	0.431	0.218	0.452	0.151	0.077	0.353

we have $h_1 = -\Delta m_1 + \Delta m_2$ and $h_2 = -\Delta m_2 + \Delta m_3$ and conduct global and multiple tests of the hypotheses (2.9), (2.10, (2.12) and (2.13) as discussed in Section .

Tables 7–10 report the *p*-values of EMaxT, MaxT, LR and D-W_∞ tests. We also report the *p*-values of usual Wald tests for two-sided tests for comparison. Note that under the hypotheses (2.12) and (2.13) EMaxT and MaxT tests collapse to univariate *t* tests when $Q^* = 1$. Also, the results for EMaxT tests under the heading "H_e" representing the *p*-values for the component statistic $n^{\frac{1}{2}}\hat{b}'\hat{\Sigma}^{-1}\hat{h}$ and that under the heading of "H_q^*" represent the ordered hypotheses with H_1^* corresponding to the smallest *p*-value. The minimum *p* -value over all components is the *p*-value for global testing of the hypotheses (2.10) and (2.13). The results of EMaxT, LR and D- W_∞ tests clearly show the strong evidence on the severity effect of child disability for single mothers regardless of whether they have an own disability or not. There is some evidence for mothers with a partner who do not have an own disability as revealed in Tables 9 and 10. The evidence becomes more significant for testing the hypotheses (2.13) which indicates some child disability in particular contributing to the evidence.

Table 8. *p*-values of testing hypotheses (2.12) and (2.13) for mothers including those having an own disability

Testing $H_q^I: h_q < 0$ or $H_Q^I: h \le 0$								
$Q^* = 2$					$Q^* = 1$	$Q^* = 3$	$Q^* = 2$	$Q^* = 1$
EMaxT			MaxT		t	LR	LR	LR
H_e	H_1^*	H_2^*	H_1^*	H_2^*	H_1^*	H_Q	H_Q	H_Q
Proposition: More severe child disability has higher negative impacts on mothers' employment								
Mothers with a partner conditional on receiving welfare								
0.432	0.681	0.657	0.668	0.641		0.547	0.339	
Mothers with a partner conditional on not receiving welfare								
						0.532		
Single mothers conditional on receiving welfare								
						0.006		
Single mothers conditional on not receiving welfare								
						0.021		
Proposition: Child disability has higher negative impacts on single mothers than mothers with a partner								
Conditional on receiving welfare								
						0.102		
Conditional on not receiving welfare								
						0.149		
Proposition: Child disability has higher negative impacts on mothers receiving welfare than mothers not receiving welfare								
Mothers with a partner								
0.778	0.974	0.347	0.974	0.336	0.188	0.477	0.350	0.217
Single mothers								
						0.137		

The *p*-values of EMaxT and MaxT tests suggest that the component $\hat{h}_1 = -\Delta\hat{m}_1 + \Delta\hat{m}_2$ contributes most to the evidence for single mothers and $\hat{h}_2 = -\Delta\hat{m}_2 + \Delta\hat{m}_3$ for partnered mothers who do not have an own disability.

Next we examine whether child disability has higher negative impacts on single mothers than mothers with a partner. The estimated results reported in Table 6 appear to suggest so; $h_q = \Delta_p m_q - \Delta_s m_q > 0, q = 1, 2, 3,$ for both the probabilities conditional on receiving or not receiving a welfare payment. The test results under the hypotheses (2.9), (2.10), (2.12) and (2.13) reported in the middle part of Tables 7–10 show some evidence particularly for mothers who do not have an own disability, but who receive welfare payments. The results of EmaxT and MaxT tests suggest that the profound child disability ($\hat{h}_1 = \Delta_p\hat{m}_1 - \Delta_s\hat{m}_1$) contributes most to the evidence.

Table 9. *p*-values of testing hypotheses (2.9) and (2.9) for mothers excluding those having an own disability

Testing $H_q{:}h_q = 0$ or $H_Q{:}\cap_{\forall q} H_q$									
EMaxT				**MaxT**			**LR**	***D-W***$_{\infty}$	**Wald**
H_e	H_1	H_2	H_3	H_1	H_2	H_3	H_Q	H_Q	H_Q
Proposition: More severe child disability has higher negative impacts on mothers' employment									
Mothers with a partner conditional on receiving welfare									
0.358	0.989	**0.116**	1.000	0.989	**0.094**	1.000	**0.060**	**0.071**	0.151
Mothers with a partner conditional on not receiving welfare									
0.431	0.997	0.139	1.000	0.997	**0.114**	1.000	**0.078**	**0.094**	0.216
Single mothers conditional on receiving welfare									
0.001	0.149	0.852	0.686	0.122	0.843	0.656	**0.000**	**0.000**	**0.004**
Single mothers conditional on not receiving welfare									
0.013	0.202	0.806	0.742	0.172	0.797	0.726	**0.009**	**0.005**	**0.047**
Proposition: Child disability has higher negative impacts on single mothers than mothers with a partner									
Conditional on receiving welfare									
0.130	**0.075**	0.887	0.282	**0.068**	0.887	0.272	**0.061**	**0.053**	0.162
Conditional on not receiving welfare									
0.239	0.133	0.917	0.396	0.123	0.917	0.388	0.122	0.102	0.290
Proposition: Child disability has higher negative impacts on mothers receiving welfare than mothers not receiving welfare									
Mothers with a partner									
0.937	0.239	0.888	1.000	0.229	0.888	1.000	0.228	0.432	0.101
Single mothers									
0.182	0.529	0.482	0.341	0.524	0.475	0.330	0.220	**0.111**	0.485

Last we examine the disincentive effect of welfare payment. As reported in Table 6, the difference between those receiving and not receiving welfare payments ($h_q = \Delta m_q(-1) - \Delta m_q(1), q = 1, 2, 3$) shows that single mothers receiving welfare are slightly less likely to work than single mothers not receiving welfare. The test results under the hypotheses (2.9), (2.10), (2.12) and (2.13) are reported in the bottom part of Tables 7–10. The results suggest some statistical evidence for single mothers, particularly by Andrews' $D\text{-}W_{\infty}$ tests. For mothers with a partner all EMaxT, MaxT, LR and $D\text{-}W_{\infty}$ tests suggest that there is no significant statistical evidence on such a welfare effect. However, *t* tests and LR tests under the one-sided hypotheses (2.12) and (2.13) reveal some evidence that profound child disability has higher negative impacts on partnered mothers receiving welfare than partnered mothers not receiving welfare; partnered mothers having a profoundly disabled child are less likely to work if they receive government welfare payments.

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Table 10. *p*-values of testing hypotheses (2.12) and (2.13) for mothers excluding those having an own disability

Testing $H_q^I: h_q < 0$ or $H_Q^I: h \le 0$								
$Q^* = 2$					$Q^* = 1$	$Q^* = 3$	$Q^* = 2$	$Q^* = 1$
EMaxT			MaxT		t	LR	LR	LR
H_e	H_1^*	H_2^*	H_1^*	H_2^*	H_1^*	H_Q	H_Q	H_Q
Proposition: More severe child disability has higher negative impacts on mothers' employment								
Mothers with a partner conditional on receiving welfare								
0.070	0.899	**0.085**	0.899	**0.064**	**0.032**	**0.082**	**0.036**	**0.000**
Mothers with a partner conditional on not receiving welfare								
0.115	0.949	**0.102**	0.949	**0.077**	**0.039**	**0.119**	**0.056**	**0.000**
Single mothers conditional on receiving welfare								
						0.002		
Single mothers conditional on not receiving welfare								
						0.022		
Proposition: Child disability has higher negative impacts on single mothers than mothers with a partner								
Conditional on receiving welfare								
0.033	0.204	**0.053**	0.191	**0.046**		**0.056**	**0.030**	
Conditional on not receiving welfare								
0.073	0.291	**0.094**	0.280	**0.084**		0.113	**0.066**	
Proposition: Child disability has higher negative impacts on mothers receiving welfare than mothers not receiving welfare								
Mothers with a partner								
0.371	0.784	0.174	0.784	0.162	**0.087**	0.267	0.178	**0.032**
Single mothers								
						0.210		

5. Conclusion

This paper constructs parametric models for estimating the effect of child disability on mothers' labor supply. We allow welfare payments to mothers to be endogenously determined with mothers' labor supply, as well as allowing child disability to account for both labor supply and welfare payment. One-sided hypothesis tests are adopted to gauge statistical evidence on several propositions that have policy relevance. Unlike past studies where welfare is treated as an exogenous variable, this paper looks at the endogeneity of welfare payments. We find that child disability restricts mothers' employment opportunities, while it increases the chances of mothers being welfare recipients.

The data we use in this study come from the survey that has a particular aim to collect information on people with a disability. Severity levels of child disability in the survey data are assessed by trained interviewers. This is in contrast to studies reported in the literature in which the lack of information concerning the measurement of child disability results in complications such as endogeneity due to self-reporting. Our data enable us to find evidence that more severe child disability has higher negative impacts on single mothers' employment. Furthermore, this paper takes into account the disincentive effect of government welfare support relating to the impact of child disability on the mother's labor supply. We also rigorously examine the differential effect of child disability on single mothers and mothers with a partner. Our study reveals some evidence suggesting child disability has a higher negative impact on single mothers than mothers with a partner. Our study also reveals some evidence on the disincentive effect of welfare payments for single mothers, as well as mothers with a partner if their child's disability is severe.

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Notes
1. Self care includes bathing or showering, dressing, eating, toileting and bladder or bowel control; mobility includes moving about the usual place of residence, getting into or out of a bed or chair, and going to or getting around a place away from the usual residence; and communication includes understanding and being understood by strangers, family and friends.
2. These people chose this reason for not working from the list that includes another eleven reasons: Not applicable; Retired; Study or returning to study; Own ill health or disability; Child care availability or children too young or prefers to look after them; Too old; Someone else's ill health or disability; Other family considerations; Pregnancy; Lack of relevant schooling, training or experience; Don't know; Other. So we exclude them from the sample on the assumption that this is a group of females who simply do not need or want to work and their absence from work is irrelevant to the health status of their own or other family members.
3. In this paper the word "partner" includes wife, husband, partner, same-sex partner.
4. The ABS data information on welfare payment is whether an individual receives any welfare payment and does not distinguish different types of payment.
5. Family income does not include mother's own income to reduce endogeneity concerns.
6. In the literature individual age is often found significantly responsible for his/her labor supply (cf. Zhang, Inder, & Zhang, 2015).

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Appendix 1

Definitions of child disability

The data used in the paper are extracted from the Survey of Disability, Ageing and Carers 2003 in which persons were identified as having a disability if they had one or more of the limitations, restrictions or impairments (listed below) which had lasted, or was likely to last, for a period of six months or more and restricted everyday activities.

- Loss of sight (not corrected by glasses or contact lenses);
- Loss of hearing where communication is restricted or an aid to assist with, or substitute for, hearing is used;
- Speech difficulties;
- Chronic or recurrent pain or discomfort that restricts everyday activities;
- Shortness of breath or breathing difficulties that restrict everyday activities;
- Blackouts, fits or loss of consciousness;
- Difficulty learning or understanding;
- Incomplete use of arms or fingers;
- Difficulty gripping or holding things;
- Incomplete use of feet or legs;
- A nervous or emotional condition that restricts everyday activities;
- Restriction in physical activities or physical work;
- Disfigurement or deformity;

- Mental illness or condition requiring help or supervision;
- Long-term effects of head injury, stroke or other brain damage that restricts everyday activities;
- Receiving treatment or medication for any other long-term conditions or ailments and still restricted in everyday activities; or
- Any other long-term condition that restricts everyday activities.

Classifications of severity of child disability

- Profound: unable to do, or always needs help with, a core activity task;
- Severe: sometimes needing assistance to perform a core activity, has difficulty understanding or being understood by family or friends, can communicate more easily using sign language or other non-spoken forms of communication;
- Moderate: not needing assistance, but having difficulty performing a core activity; and
- Mild: needing no assistance and having no difficulty performing a core activity, but uses aids or equipment because of disability, cannot easily walk 200 m, cannot walk up and down stairs without a handrail, cannot easily bend to pick up and object from the floor, cannot use public transport, can use public transport but needs help or supervision, needs no help or supervision but has difficulty using public transport;
- Not limited: not limited in core activities, but may have school or employment restrictions.