Children and Women's Participation Dynamics: Transitory and Long-Term Effects*

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Abstract

Children affect the after-birth labor force participation of women in two ways. Directly, the time spent in child-care reduces the labor market effort. The time spent out of the labor market while on maternity leave alters women's participation experience and, thus, indirectly affects subsequent participation behavior. This paper proposes a model that disentangles the direct and indirect effect of children on women's labor force participation, and evaluates their relative importance. Participation decisions for three levels of labor market involvment - employed full-time, employed part-time, not employed - are represented by a multivariate probit model with a general correlation structure. The model allows for a high degree of flexibility in modeling the dependence of sequential decisions. The estimation is performed using Markov chain Monte Carlo methods. It is shown that the indirect effect, through time out of the labor market, is more important. The direct effect wanes with the age of the child. The indirect effect grows with the length of the interruption.

Keywords: Female Labor Supply, Multivariate Probit Model, Gibbs Sampler.
JEL codes: C11,C15, J13, J22

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1 Introduction

The effects of children on women's labor force participation have often been studied in labor economics. The literature spans most of the last four decades and has paralleled the political debate which led to significant changes in the structure of social policies regarding maternity and child care. The departing point was the recognition that children reduce women's labor supply and that the magnitude of this effect decreases with the age of the youngest child (for example, Mincer, 1962, Mincer and Polachek, 1974)[1]. Initial cross-section evidence confirmed this hypothesis. Furthers studies using short panel data indicated that women have a continuous labor supply. The majority either work for most of their active life or do not work at all, and participation in one period altered the participation probability in future periods (Heckman and Willis, 1978, Nakamura and Nakamura, 1985, Hyslop, 1999). When accounted for, this dependence significantly changed the estimated effects of children on labor supply. Subsequent studies provided mixed evidence on the magnitude of the child effect. Nakamura and Nakamura (1985, 1994) found that, when controlling for previous period's labor supply, the effect of children on present labor supply disappears. Moreover, using additional information on labor supply of more distant past has no effect. Challenging their results, Duleep and Sanders (1994), found that children affect negatively the labor supply of women with strong labor market attachment. Despite conflicting results, all studies underscored the importance of unobserved heterogeneity as a determinant of labor supply and of the effect of children on labor supply. The policy implication of an overriding effect of unobserved heterogeneity on labor supply cannot be understated. If unobserved heterogeneity reflects unobserved ability and different preferences over family and career, time spent out of the market around birth will have little effect on subsequent employment probability. Hinting to a more complex process, Shapiro and Mott (1994) provide evidence that work attachment around birth is a good predictor of subsequent labor supply.

European literature was to a large extent driven by the institutional differences between the US and Western Europe, the differences among European countries, and the changes in legislation regarding maternity and parental leave. The rich set social policies and institutional settings allowed the identification and evaluation of the effects of a wide range of factors on women's labor supply around birth: the structure of the tax and benefit system, the existence of day-care subsidies and availability of quality child care, the dura-

[1] Early empirical evidence was provided by Hotz and Miller (1988), Heckman and Willis (1975), or Moffit (1984).

tion and replacement ratio of maternity and parental leaves, the organization of school day and availability of after-school care, the availability of part-time jobs, regulations regarding leaves for caring for sick children, etc. Gustafsson et al. (1996) provide a comprehensive comparison of social policies and their effect on women labor force participation in Great Britain, Germany, and Sweden. Changes in German legislation regarding maternity and parental leaves have been used by Ondrich, Spiess, and Young (1996) to assess the effect of length and level of maternal and parental benefits on the length of labor work interruptions.

This paper proposes a different approach for estimating the effect of children on women's labor market behavior. Although many different interpretations are possible we can classify them into two broad channels. The *direct* effect[2] captures the reduced probability of working part time or full time for women with children. This effect is consistent with models where mother's market effort diminishes as the child-care time increases (Becker, 1985). The *indirect* effect operates through the effect of time out from the labor market, which is correlated with family structure. This effect could be interpreted in a model framework in which wages and participation depend on experience and job seniority. Interruptions affect these factors and will subsequently have an effect on labor market outcomes (e.g. Blau and Ferber, 1991).

We use panel data on the German labor market to investigate the dynamic patterns of labor market involvement of married women and analyze the effect of family structure - number of children and age distribution - on women's labor market behavior. The empirical specification allows us to disentangle the direct and indirect effect of children on mother's labor force participation. Participation decisions with three states of labor market involvement - full time work , part-time work, and nonwork - are represented by a multivariate probit model with a general correlation structure. This model allows for a high degree of flexibility in modeling the dependence of decisions, both across choices and over time. It also avoids strong assumptions about preferences[3].

Lately, two-state models of labor force participation have been estimated using maximum simulated likelihood (Hyslop, 1999). Due to the difficulty in estimation, three-state models have been rarely used in empirical studies. However, the level of labor market involvement plays an important role in labor market dynamics. Studies analyzing transition matrices or using competing risks models show that past and current participation decisions are

[2]Dankmeyer (1996) uses the terms direct and indirect effect in the sense of opportunity costs of having children and computes their value.

[3]In contrast, the multinomial logit or probit model assumes that individual's preferences are defined over entire labor market histories (e.g. Chintagunta, 1992).

strongly correlated and part-time jobs rarely represents a first step toward full-time jobs (for example, Blank, 1989, 1994 for the US and Giannelli, 1996, using German data). In this paper we use a Bayesian Markov Chain Monte Carlo (MCMC) method, introduced by Chib and Greenberg (1998), to estimate the multivariate probit model. This method avoids the convergence problems that hamper the maximum likelihood estimation.

Consistent with previous studies, we find that women's labor market histories display a remarkable continuity. The choice of labor market states is strongly persistent. For most individuals part-time employment does not constitute a state of transition toward full-time jobs. The direct effect of children on women's labor supply is significant and declines with the age of the child. The indirect effect is larger than the direct effect and increases with the length of the interruption. The choice of labor market states is persistent around birth-related interruptions. Most women will return to their previous state. Those with high education, however, are relatively more likely to enter full-time time employment following birth interruptions, regardless of the pre-birth state.

The remainder of the paper is structured as follows. Section 2 contains a theoretical background and a description of the data. The empirical specification and the estimation method are presented in section 3. Section 4 gives the formal definition of the direct and indirect effects and describes the simulation strategy employed to calculate them. The discussion of the results and concluding remarks follow.

2 Theoretical background and data

The existing literature on women labor supply suggests two basic facts. First, children have a negative effect on women's labor supply. The effect fades away as children grow older. Many different causes play a part. Women's physical capacity of performing market work is sharply diminished during the period surrounding birth; rearing children requires time-intensive care and is a taxing personal and family adjustment process. As children grow, caring for them requires less time and women find better ways of dealing with the children and family needs. This effect can be formalized and studied using various models. The neoclassical labor supply theory assumes that individuals make employment decisions by comparing the utility of working with the utility of not working. The value of not working relative to working declines as the child ages (Mincer 1962, Heckman 1980, Leibovitz, Lerman and Waite 1992). In a job-search framework (Mortensen, 1986) the value of time in alternative (non-work) use can be assumed to vary with the number of children and their ages. The birth of the child will raise the value of time in alternative use and, through it, the reservation wage. As a result, the probability of employment will decline.

The second fact is that sequential employment decisions of women are correlated. As a result, labor market interruptions lower the employment probability in subsequent periods. Heckman and Willis (1978) have defined two sources of dependence: a) unobserved heterogeneity generated by different preferences, and b) state dependence. There are multiple sources of state dependence. Human capital theory predicts that skills accumulated through experience raise the probability of working in the future. Fixed costs of entering the labor force (search costs, for example) make future participation more likely for individuals already working. Job matching models where employers and employees learn about the quality of the match induce state dependence even if investment in firm-specific human capital does not take place. Unobserved heterogeneity alone carries no strong implication of work interruptions. The presence of state dependence, however, is very important in studying the effect of fertility on labor supply. In the appropriate models, maternity-related work interruptions lead to lapses in the process of investment of human capital, and, possibly to depreciation of the human capital stock, search costs and information on the quality of the match may be lost. Longer interruptions are more detrimental in the human capital framework.

These two facts provide the optimal framework for studying the effect of children on women's labor supply. They imply that a women's post-birth employment likelihood should be driven by the increased demand placed on mothers time by newborn children and by the length of the maternity-related work interruption. The first component should be fading with child's age. The second component should be stronger the longer the interruption, as implied by human capital investment models. In this paper we use the broad labels direct and indirect effects for these two mechanisms. The measures of the direct and the indirect effect depend on the events for which they are measured. In the next section we restrict ourselves to a set of events of interest and provide the strict definitions of the direct and indirect effects for these particular events.

Germany offers the appropriate environment for studying the effect of children on women's labor force participation and assessing the relative importance of the direct and indirect effect[4]. The parental leave and benefit policies are among the most generous among the industrialized countries. The prevailing institutional settings are based on a bread-winner ideology. The tax system benefits one-earner families. There is very little full-day care, but high quality part-day care, subsidized by local government, is available. School day is organized assuming that the parent will help with the heavy school homework children are supposed to carry out in the afternoon. Components of maternal leave and benefit policy include: special protection against dismissal during pregnancy and 4 months after delivery; an 8 week period after birth during which mothers are not allowed to work; a protected maternity leave which, including the 8 weeks immediately following birth, lasts for 36 months; child rearing benefit for parents not involved in full-time work, independent of the previous employment status, for a period of 24 months.

Generous policies induce mothers to drop out of the labor market for a longer period of time. As a result, the factors influencing the indirect effect are likely to play an important role. Not surprisingly, it has been showed that even among women who work prior to giving birth, the incidence of returning to market work in Germany is lower than in countries with less generous social policies.

We use data from five waves of the German Socio-Economic Panel (GSOEP), for the years 1994 to 1998. We restrict ourselves to a balanced panel of all women between the ages of 25 and 65 who are either married or living in consensual union[5]. This results in 2,576 individuals or 12,880 person-year observations. Tables 1 and 2 contain some of the mean characteristics of the

[4]The relative importance of the direct and indirect effects of children on women's labor supply is strongly influenced by institutional settings. Since we are not controlling for the institutional setting, the findings can be extrapolated only with caution to labor markets characterized by contrasting social policies.

[5]For a good discussion on the GSOEP data in general see for instance the paper by

sample. Approximately half the married women between the age of 25 and 65 work and when they work they are about twice as likely to work full-time than part-time. In general younger women and women with a higher education work more often.

When we compare women without children and women with a young child we observe a virtual collapse of the incidence of working full time, but we do not find any noticeable drop with regards to working part time for either medium educated young women or highly educated older women. In general, the reduced incidence of working part time is much less dramatic than what we observe for full time. Women with older children are even more likely to be working part time than women without children. Overall, total employment rates for women without children are always higher. A rough sketch of the dynamics is captured in the five transition matrices in figure A, indicating movements between labor states from one wave to the next and from the start to the end of the sample[6].

Wagner, Burkhauser and Behringer (1993).

[6]Shorrocks (1978) defines $\frac{(n-trace(P))}{(n-1)}$ as a measure of mobility, where n is the number of states and P is the transition probability matrix. This measure is naturally bounded between 0 (immobility) and 1 (perfect mobility). We find year to year transitions to have a mobility measure of 0.3. When looking at the transitions from the beginning (wave 1) to the end (wave 5) we find a mobility measure of 0.5. For comparison, Boeri and Flinn (1999) find a measure of 0.2 for occupational mobility in Italy during the mid to late nineties, when looking at quarterly transitions and classifying nine occupation categories.

3 Empirical specification

The main goal of this paper is to disentangle the direct and indirect effects of children on women's level of labor market involvement. Our empirical strategy entails several components. First, we choose a specification for the cost of raising children. Second, we construct a model of labor market decisions which explicitly accounts for the dependence of sequential decisions and allows three levels of labor market involvement. Finally, simulations scenarios of different family composition and labor market histories are used to measure the direct and indirect effects of children on a set of events of interest. The dependence of sequential decisions allows us to separate the effect of time out of the market and direct effect of children.

The measurement of the direct and indirect effect relies on using an appropriate representation of the cost of raising children. The cost of raising children depends on the number of children and children's age distribution. Specifications previously used were based on the age of the youngest child, the number of children, or the number of children in certain age categories. The latter specification, also employed in this paper, provides a more precise description of the age distribution. We follow Hyslop (1999) in defining the following age categories; [0,3), [3,6), [6,17), and [17,..). This specification has the advantage of separating pre-school and school-age children. It further breaks the pre-school age in two categories that are generally associated with different care needs.

The level of labor market involvement plays and important role in labor market dynamics. There is abundant evidence that women maintain a remarkably stable level of labor market involvement. Part-time work represents a qualitatively different state: it is less persistent than full-time work and nonwork; for different categories of individuals, it represents an alternative to full-time work or to nonwork; it rarely becomes a stepping-stone into full-employment for women who have been absent from the labor market. Changes in the number of children and children's ages are major determinants of changes in labor market status. Part-time may play an important role in returning to the market after birth. It is therefore important to include part-time in a study about the effect of children on women's labor supply.

We use a random utility model to represent individual labor market experiences in this three-dimensional state space. In this setting individuals choose, every time period, among three alternative states: full time, part time or not employed. Let the utility associated with each state be denoted by Z_{it}^{ft}, Z_{it}^{pt}, and Z_{it}^{nw}, respectively. The utility levels in each state are a function of personal characteristics and household composition. For each state,

$Z^{\cdot\cdot}_{it}$, we specify the following utility function

$$Z^{\cdot\cdot}_{it} = \alpha^{\cdot\cdot} + \beta^{\cdot\cdot}_1 * \text{Age}_{it} + \beta^{\cdot\cdot}_2 * \text{Age}^2_{it} + \beta^{\cdot\cdot}_3 * \text{Age}^3_{it} +$$

$$+ \beta^{\cdot\cdot}_4 * I(\text{Educ1}_{it}) + \beta^{\cdot\cdot}_5 * I(\text{Educ2}_{it}) + \beta^{\cdot\cdot}_6 * Log(\text{NonWageInc}_{it}) +$$

$$+ \beta^{\cdot\cdot}_7 * Log(\text{SpouseWage}_{it}) + \beta^{\cdot\cdot}_8 * I(\text{SpouseParticitation}_{it}) +$$

$$+ \beta^{\cdot\cdot}_9 * \text{Kids0-3}_{it} + \beta^{\cdot\cdot}_{10} * \text{Kids3-6}_{it} + \beta^{\cdot\cdot}_{11} * \text{Kids6-17}_{it} + \beta^{\cdot\cdot}_{12} * \text{Kids>17}_{it} + u^{\cdot\cdot}_{it}$$

where I($\cdot$) represents the indicator function. The subscript i indicates individuals and subscript t indicates time period.

The effect of age on the utility of a given level of labor market involvement is captured by a polynomial component of degree three. We control for the level of education[7], non-wage income, and spouse's labor market participation and wage. The variables KidsX-Y represent the number of children with ages within the respective ranges.

Models of multiple individual decisions fall in one of the following three categories: different decisions are made by the same individual at a given time, the same decision is made sequentially, or several different decisions are repeated over time. If several different decisions are observed over time the number of dependencies that need to be modelled becomes large. The estimation by maximum likelihood becomes increasingly difficult, as higher level multiple integrals have to be evaluated within each step of the maximization routine. The solution generally involves the use of random effects to model the dependence across sequential decisions. The main drawback of this approach is that it imposes a constant correlation between sequential decisions. When the multivariate logit model is used to model contemporary decisions, it imposes the additional restriction that the random utilities corresponding to each choice are independent.

We assume that, every time period, individuals draw realizations of the three latent variables from a known joint distribution given by:

[7] We specify three educational classes representing the highest general education level completed. The variable Educ0, Educ1 and Educ2 represent high, medium and low education, respectively. They correspond to the International Standard Classification of Education (ISCED). Educ2 represents pre-primary, primary and lower secondary education. Educ1 represents (upper) secondary education. Educ0 represents tertiary education.

$$
\begin{aligned}
Z_{it}^{ft} &= X_i \beta_t^{ft} + u_{it}^{ft} \\
Z_{it}^{pt} &= X_i \beta_t^{pt} + u_{it}^{pt} \\
Z_{it}^{nw} &= X_i \beta_t^{nw} + u_{it}^{nw}
\end{aligned}
$$

where u_{it}^{ft}, u_{it}^{pt},and u_{it}^{nw} have a joint multivariate normal distribution. The dimension of the distribution is $3T$, where T is the number of waves in the panel. Let $u_{it} = \left[u_{it}^{ft} | u_{it}^{pt} | u_{it}^{nw} \right]$. $E\left[u_{it}\right] = 0$, u_{it} are independent over i and it has a correlation structure over t given by a general $3T$ x $3T$ correlation matrix. The number of free elements in the correlation matrix is $3T$ $(3T-1)/2$.

The state choice is represented by a set of binary variables defined in the following way:

$$
\begin{aligned}
y_{it}^{ft} &= 1 \text{ if } Z_{it}^{ft} > 0, Z_{it}^{pt} < 0, \text{and } Z_{it}^{nw} < 0 \\
y_{it}^{pt} &= 1 \text{ if } Z_{it}^{pt} > 0, Z_{it}^{ft} < 0, \text{and } Z_{it}^{nw} < 0 \\
y_{it}^{nw} &= 1 \text{ if } Z_{it}^{nw} > 0, Z_{it}^{ft} < 0, \text{and } Z_{it}^{pt} < 0
\end{aligned}
$$

Let $y_{it} = [y_{it}^{ft} | y_{it}^{pt} | y_{it}^{nw}], y_i = [y_{i1} | y_{i2} | ... | y_{iT}], y = [y_1 | y_2 | ... | y_n]$ and, similarly, $Z_{it} = [Z_{it}^{ft} | Z_{it}^{pt} | Z_{it}^{nw}], Z_i = [Z_{i1} | Z_{i2} | ... | Z_{iT}], Z = [Z_1 | Z_2 | ... | Z_n]$.

This structure closely resembles that of a multivariate probit model. The major difference is that the vector y is restricted to a subset of all possible combinations of values. Any time period, an individual can be in one, and only one, state. This means that, in any time period, only three combinations of values are feasible out of a total of eight[8]. This induces an additional truncation for the joint distribution of Z_i. Not only is the distribution of each component restricted by the value of the corresponding discrete dependent variable, but the joint distribution is further truncated to the space of feasible combinations for the components of y_i. To estimate this model, we use an extension of the Markov chain Monte Carlo algorithm introduced by Chib and Greenberg (1998), which deals specifically with this additional truncation. The algorithm is presented in the appendix. Predictions made on the basis of the results are adjusted to account for this additional truncation.

The random utility model does not impose strong assumptions on individual preferences. It does not impose an a priori ordering of choices and

[8] To see this point, let y_{it}^{ft}, y_{it}^{pt} and y_{it}^{nt} take on only two possible values, being 0 or 1. This generates $2^3 = 8$ possible combinations of $(y_{it}^{ft}, y_{it}^{pt}, y_{it}^{nt})$. However, only (1,0,0), (0,1,0) and (0,0,1) are feasible.

allows part-time to be modelled as a qualitatively different state. The truncated multivariate probit model we use in this paper allows for a general correlation structure, both across choices and over time. In this respect it is the most general framework we are aware of. As the estimated model is not structural, it is less important to break down dependence into state dependence and unobserved heterogeneity. However, in this framework, the effect of past status on the present decision can be estimated using simple conditional probabilities. This approach is more general than the usual method of using lagged dependent variables in the present decision. It does not suppress the dependence beyond the immediate past status and allows for a more general dependence than the simple linear relationship between the past status and the expected value of the current latent dependent variable.

In a cross-sectional study with this specification, identification of the effect of children in a given age category would come from comparing women with different number of children in the respective category. As a result, the coefficients of the children variables measure the total effect including both the cost of raising the child at that point in time and the consequences on labor market interruptions while raising the child up to that age. Panel data allow the modelling of the dependence of sequential labor force participation decisions. The effect of employment in the previous years is observed and accounted for by the dependence in sequential decisions. In addition, if one observes the history of labor force participation decisions, the variation in post-birth employment decisions can be used to identify the direct and indirect effect. Using the dependence, and variation in post-birth histories, we can calculate the total effect as the difference between the probability of participation conditional on family structure and participation history.

4 Direct and indirect effects

The computation of the direct and indirect effects is based on simulation scenarios with several distinct components. First, in all our simulation scenarios, we assume that the labor market state in wave 1 is full-time. This assumption has two implications. It reduces the scope and the confounding effect of unobserved heterogeneity in studying subsequent labor market outcomes. Secondly, it influences the magnitudes of the direct and the indirect effects as well as the effects of other personal characteristics on labor market decisions. Past labor market status influences present decisions in a way determined by the estimated correlation between sequential decisions. The nonlinearity of the normal CDF implies that the effect of personal characteristics will be different for different labor market histories.

The values chosen for the personal characteristics allow us to construct age profiles for the probabilities of any even of interest. Results are compared across educational levels.

Personal characteristics	Values used in simulation
Age	25,27,...65 (19 values)
Education	Low, Medium, High
Non-wage income	0
Spouse's wage	median
Spouses LM status	working

Measuring the direct and the indirect effect of children rests on generating the appropriate fertility history. It is important to note that children enter this model in a special way. A children born in a given year will change the variables that describe the number of children and the age distribution in all subsequent years. Two processes happen simultaneously: labor market decisions affect labor market history, and children grow older. To describe the dynamic behavior of the direct and indirect effects, we need to simulate both a case where the child's age evolves naturally, and a case where age is held constant. We use the following scenarios.

Scenario	Wave1		Wave2		Wave3		Wave4		Wave5	
	No.	Age	No.	Age	No.	Age	No.	Age	No.	Age
1	0	-	0	-	0	-	0	-	0	-
2	0	-	1	0-2	1	0-2	1	0-2	1	3-5
3	0	-	1	0-2	1	0-2	1	0-2	1	0-2

These scenarios allow us to calculate the effect of *one* child born in wave two on the labor market behavior. To keep the exposition simple we do not extend the present analysis to the second or subsequent children. The extension is straightforward and one interesting aspect deserves attention. The empirical specification we propose assumes that the effect of children in a given age category on the *utility* is linear in the number of children. This linear relationship translates into a non-linear effect on the probability of a given event, due to the non-linearity of the normal CDF function. For example, the effect of a new born child on the probability of working full-time is likely to be smaller for women who already have a child. We also restrict our attention to the effect of children on the probability of working *full-time* after birth. A similar strategy can be applied if the labor market state prior to birth is different or for different post-birth destinations.

Let FT_x and NW_x denote working full-time and nonwork in wave x, respectively. In wave 2 there is no indirect effect (IE) as no time has been taken out of the labor market. The total effect (TE) is computed by comparing the probability of working full-time in wave 2 conditional on having worked full-time in wave 1 for a person with a child age 0-2 (K_{0-2}) in wave 2 and a person with no children (noK).

$$TE_2 = DE_2 = \Pr(FT_2|FT_1,\ \mathrm{K}_{0\text{-}2}) - \Pr(FT_2|FT_1,\ \mathrm{noK})$$

In wave three, the reference point will be the person who did not have a child (scenario 1) and continued to work full-time in wave 2. The total effect in wave 3 will measure the distance between this reference point and a person that had a child in wave 2 (scenario 2) and did not work in wave 2. The direct and indirect effects are calculated by adding and subtracting the conditional probability of working full-time in wave 3 conditional on having a child in wave 2 and working full-time in wave 2. The direct effect measures the effect of a child age 0-2 on the probability of working full-time in wave 3, conditional on working full-time in wave 2. The indirect effect measures how one year out of the market affects employment probability of a person with a child age 0-2.

$$\begin{aligned}
TE_3 &= \Pr(FT_3|FT_1, FT_2, \mathrm{noK}) - \Pr(FT_3|FT_1, NW_2, \mathrm{K}_{0\text{-}2}) \\
DE_3 &= \Pr(FT_3|FT_1, FT_2, \mathrm{noK}) - \Pr(FT_3|FT_1, FT_2, \mathrm{K}_{0\text{-}2}) \\
IE_3 &= \Pr(FT_3|FT_1, FT_2, \mathrm{K}_{0\text{-}2}) - \Pr(FT_3|FT_1, NW_2, \mathrm{K}_{0\text{-}2})
\end{aligned}$$

The total, direct, and indirect effects are measured the same way for wave 4.

$$\begin{aligned}
TE_4 &= \Pr(FT_4|FT_1, FT_2, FT_3, \mathrm{noK}) - \Pr(FT_4|FT_1, NW_2, NW_3, \mathrm{K}_{0\text{-}2}) \\
DE_4 &= \Pr(FT_4|FT_1, FT_2, FT_3, \mathrm{noK}) - \Pr(FT_4|FT_1, FT_2, FT_3, \mathrm{K}_{0\text{-}2}) \\
IE_4 &= \Pr(FT_4|FT_1, FT_2, FT_3, \mathrm{K}_{0\text{-}2}) - \Pr(FT_4|FT_1, NW_2, NW_3, \mathrm{K}_{0\text{-}2})
\end{aligned}$$

One should note that, due to the way we constructed the children variables, the age category of a child does not change between waves 2 and 4. In a sense, the direct and indirect affects are measured for constant age. In wave five, a child born in wave 2 will move to the age category 3-5. With the total, direct, and indirect effects measured as before, the age change has a potential confounding effect. It is no longer possible to compare the indirect effects across waves to infer the effect of the additional year out of the labor market because the difference compounds the effect of the age change. The fact that the age category has in fact changed prevents us from making any inference about the variation in the direct effect with the child's age. Also, any comparison based on waves 3 and 4 will be affected by the different histories. To solve these two problems (inference about the changes of the indirect effect with time out of the market and the direct effect with child's age) in wave 5 we use scenario 3 - child of constant age - as a counterfactual.

As before, the total, direct and indirect effects in wave 5 are:

$$\begin{aligned}
TE_5 &= \Pr\left(FT_5|FT_1, FT_2, FT_3, FT_4, \text{noK}\right) - \Pr\left(FT_5|FT_1, NW_2, NW_3, NW_4, \text{K}_{3\text{-}5}\right) \\
DE_5 &= \Pr\left(FT_5|FT_1, FT_2, FT_3, FT_4, \text{noK}\right) - \Pr\left(FT_5|FT_1, FT_2, FT_3, FT_4, \text{K}_{3\text{-}5}\right) \\
IE_5 &= \Pr\left(FT_5|FT_1, FT_2, FT_3, FT_4, \text{K}_{3\text{-}5}\right) - \Pr\left(FT_5|FT_1, NW_2, NW_3, NW_4, \text{K}_{3\text{-}5}\right)
\end{aligned}$$

Holding the age category constant in wave 5 the total, direct, and indirect effects become

$$\begin{aligned}
\overline{TE}_5 &= \Pr\left(FT_5|FT_1, FT_2, FT_3, FT_4, \text{noK}\right) - \Pr\left(FT_5|FT_1, NW_2, NW_3, NW_4, \text{K}_{0\text{-}2}\right) \\
\overline{DE}_5 &= \Pr\left(FT_5|FT_1, FT_2, FT_3, FT_4, \text{noK}\right) - \Pr\left(FT_5|FT_1, FT_2, FT_3, FT_4, \text{K}_{0\text{-}2}\right) \\
\overline{IE}_5 &= \Pr\left(FT_5|FT_1, FT_2, FT_3, FT_4, \text{K}_{0\text{-}2}\right) - \Pr\left(FT_5|FT_1, NW_2, NW_3, NW_4, \text{K}_{0\text{-}2}\right)
\end{aligned}$$

Using these intermediary results, we can compute the change in the direct effect when the age of the child changes.

$$\Delta DE = \overline{DE}_5 - DE_5$$

Note that the probabilities are calculated conditional on the same work history. The change in the indirect effect for one extra year out of the market (from 2 to 3 years) can be calculated as

$$\Delta IE = \overline{IE}_5 - IE_4$$

The probabilities are conditional on having one child in age category 0-2.

Under weak assumptions, the model yields predictions consistent with the relevant theoretical models. Controlling for previous employment history, the direct effect of children on employment probability decreases with children's ages. Holding children's ages constant, the indirect effect grows with time spent nonworking. Constant-age changes of the indirect effect can be calculated in two situations. Between waves 3 and 4, the child born in wave 2 remains in the age category 0-2. The change in the indirect effect is

$$\begin{aligned} IE_4 - IE_3 &= [\Pr(FT_4|FT_1, FT_2, FT_3, \mathrm{K}_{0\text{-}2}) - \Pr(FT_4|FT_1, NW_2, NW_3, \mathrm{K}_{0\text{-}2})] - \\ &\quad - [\Pr(FT_3|FT_1, FT_2, \mathrm{K}_{0\text{-}2}) - \Pr(FT_3|FT_1, NW_2, \mathrm{K}_{0\text{-}2})] \\ &= [\Pr(FT_4|FT_1, FT_2, FT_3, \mathrm{K}_{0\text{-}2}) - \Pr(FT_3|FT_1, FT_2, \mathrm{K}_{0\text{-}2})] + \\ &\quad + [\Pr(FT_3|FT_1, NW_2, \mathrm{K}_{0\text{-}2}) - \Pr(FT_4|FT_1, NW_2, NW_3, \mathrm{K}_{0\text{-}2})] \end{aligned}$$

The terms in the right-hand side of the equation are both positive if the utilities of working full-time and nonworking are, respectively, positively correlated over time and if they are negatively correlated to each other. We do expect this to be the case given previous findings that the choice of labor market involvement levels are persistent. We expect the indirect effect to increase with time out of the labor market. Between waves 4 and 5 the age category changes from 0-2 to 3-5. The change in the indirect effect becomes

$$\begin{aligned} IE_5 - IE_4 &= [\Pr(FT_5|FT_1, FT_2, FT_3, FT_4, \mathrm{K}_{3\text{-}5}) - \Pr(FT_5|FT_1, NW_2, NW_3, NW_4, \mathrm{K}_{3\text{-}5})] - \\ &\quad - [\Pr(FT_4|FT_1, FT_2, FT_3, \mathrm{K}_{0\text{-}2}) - \Pr(FT_4|FT_1, NW_2, NW_3, \mathrm{K}_{0\text{-}2})] \\ &= [\Pr(FT_5|FT_1, FT_2, FT_3, FT_4, \mathrm{K}_{3\text{-}5}) - \Pr(FT_4|FT_1, FT_2, FT_3, \mathrm{K}_{0\text{-}2})] + \\ &\quad + [\Pr(FT_4|FT_1, NW_2, NW_3, \mathrm{K}_{0\text{-}2}) - \Pr(FT_5|FT_1, NW_2, NW_3, NW_4, \mathrm{K}_{3\text{-}5})] \end{aligned}$$

The term in the first parenthesis is positive if full-time is a persistent state (positive autocorrelation) and if the effect of children declines with age - both hypotheses are reasonable. The sign of the second term is ambiguous, as one extra nonworking year reduces the probability of working full-time, while an older child will increase it. The two effects can be further separated by writing the second term as:

$$\begin{aligned} & \Pr(FT_4|FT_1, NW_2, NW_3, \mathrm{K}_{0\text{-}2}) - \Pr(FT_5|FT_1, NW_2, NW_3, NW_4, \mathrm{K}_{3\text{-}5}) \\ = \; & [\Pr(FT_4|FT_1, NW_2, NW_3, \mathrm{K}_{0\text{-}2}) - \Pr(FT_5|FT_1, NW_2, NW_3, NW_4, \mathrm{K}_{0\text{-}2})] + \\ & + [\Pr(FT_5|FT_1, NW_2, NW_3, NW_4, \mathrm{K}_{0\text{-}2}) - \Pr(FT_5|FT_1, NW_2, NW_3, NW_4, \mathrm{K}_{3\text{-}5})] \end{aligned}$$

The first term is the age-constant change in the indirect effect ΔDE and is positive if the utility of working full-time is negatively correlated with the utility of not working. The second term is negative if older children reduce the utility of working full-time by less. The magnitudes of the two opposite effects depend on the other personal characteristics and the change in the indirect effect can assume positive or negative values across individuals with different ages, education levels, and family characteristics.

The change in the direct effect with the age of the child can be calculated comparing the direct effects in waves 4 and 5.

$$\begin{aligned} DE_5 - DE_4 &= [\Pr(FT_5|FT_1, FT_2, FT_3, FT_4, \text{noK}) - \Pr(FT_5|FT_1, FT_2, FT_3, FT_4, \text{K}_{3\text{-}5})] - \\ &\quad - [\Pr(FT_4|FT_1, FT_2, FT_3, \text{noK}) - \Pr(FT_4|FT_1, FT_2, FT_3, \text{K}_{0\text{-}2})] \\ &= [\Pr(FT_5|FT_1, FT_2, FT_3, FT_4, \text{noK}) - \Pr(FT_4|FT_1, FT_2, FT_3, \text{noK})] + \\ &\quad + [\Pr(FT_4|FT_1, FT_2, FT_3, \text{K}_{0\text{-}2}) - \Pr(FT_5|FT_1, FT_2, FT_3, FT_4, \text{K}_{3\text{-}5})] \end{aligned}$$

The first term is unambiguously positive as one extra year worked full-time will increase the probability of working full-time. The second term is negative because both the extra year worked full-time and older children increases the probability of working full-time. We rewrite the second term as

$$\begin{aligned} &\Pr(FT_4|FT_1, FT_2, FT_3, \text{K}_{0\text{-}2}) - \Pr(FT_5|FT_1, FT_2, FT_3, FT_4, \text{K}_{3\text{-}5}) \\ = &[\Pr(FT_4|FT_1, FT_2, FT_3, \text{K}_{0\text{-}2}) - \Pr(FT_5|FT_1, FT_2, FT_3, FT_4, \text{K}_{0\text{-}2})] + \\ &+ [\Pr(FT_5|FT_1, FT_2, FT_3, FT_4, \text{K}_{0\text{-}2}) - \Pr(FT_5|FT_1, FT_2, FT_3, FT_4, \text{K}_{3\text{-}5})] \end{aligned}$$

The first part is the (uninteresting) age constant change in the direct effect and it is negative. The second term is the effect of a change in the child's age keeping history constant (the cleanest form of direct effect) and it is also negative if older children raise that utility of working full-time.

5 Findings and discussion

5.1 General considerations

For each parameter, we report the moments of the posterior distribution, the numerical standard error of the estimated mean (which accounts for dependence of successive draws) and evaluate the convergence of the MCMC algorithm. We estimate six sets of slope coefficients. For every labor market state, we estimate an initial set for the first wave and a second set for the subsequent waves 2 to 5. We also estimate the 105 free elements of the correlation matrix[9]. Tables 3, 4, and 5 report the posterior means, posterior standard deviation (PSTD), numerical standard errors (NSE), and scale reduction factors (R) for the three levels of labor market involvement. The values of R very close to 1 indicate convergence. Table 6 reports the posterior means for the correlation coefficients.

Coefficient estimates measure the effect of the independent variables on the values of the utility functions associated with the three labor market states. Age has near-linear effects on the three utilities for the age range of interest. Younger women are more likely to work full-time. Higher education raises the utility of working full-time and lowers the utilities associate with part-time work and no work. Spouse's wage has a negative effect on the utility of a full-time job and positive effects on the utility of part-time and non-working. Spouse's participation and wage have opposite signs on utilities associated with all three states. The utility of working full-time increases for low levels of spouse's wage and falls bellow the level corresponding to a non-working husband as the wage increases. The effects on part time and non-working are reversed. The presence of children reduces the utility of working full-time; the effect is smaller for older children. At the same time children increase the utility of not working. The effect on the utility of working part-time is the most interesting. Very young children reduce the utility of working part-time. Older children make part-time more desirable. The maximum is attained for school-age children. It seems that women prefer to take part-time jobs when children go to school. This is consistent with our expectations given the lack of after-school care and the structure of the school day.

[9]Recall that the symmetric σ-matrix had 3T*(T-1)/2 free off-diaginal correlations, where T equals the number of periods. In our case T=5. Also note that we do not superimpose a structure on the correlation matrix other than the restriction that all elements lay within the interval [-1,1] and that the is matrix positive definite at all times.

The correlation matrix provides a very rich description of the stochastic process driving labor market histories. The diagonal blocks describe the autocorrelation of the three utility functions. The correlation coefficients in these blocks are high and decline with the length of the time interval. This indicates the presence of unobserved heterogeneity (the limit of the correlation coefficients) and autocorrelated error terms. Using only random effects would not have been appropriate. The strongest persistence is displayed by full-time and non-work states. The lower correlation coefficients of part-time indicate that, while still persistent, part-time has a different nature (different type of employment). The magnitudes of the blocks off the diagonal underscore this finding.

The elements of the off-diagonal blocks are all negative. The shape of the blocks over time is similar - the diagonal elements are stronger, the off-diagonal elements fade with the time interval. This shows that the dependence is based on something else in addition to unobserved heterogeneity. Maybe the sharpness of this shape is indicative of the degree to which the negative correlation is driven by unobserved heterogeneity. The shape of the correlation matrix is consistent with a stochastic process characterized by negatively correlated state-specific random effects and a multivariate normal AR(1) process, for example. Part-time is closer then full-time to non-work . The negative correlation between full-time and non-work is stronger than between part-time and non-work.

After having estimated the parameters of the model, we compute the probabilities for all possible labor market histories[10]. The probabilities are evaluated at one hundred points chosen randomly from the thinned posterior distribution of the parameters. We use these probabilities to construct high posterior density intervals of life cycle profiles for selected events. The graphs of the life cycle profiles provide a much clearer understanding of the results and subsequent discussion is entirely based on them.

5.2 The role of part-time employment

The estimated correlation matrix shows that choice of part-time is remarkably stable, albeit least stable among the three states of labor market involvement. Its stability implies that part-time is unlikely to represent a bridge

[10]In a five-period three-state model, there are $3^5 = 243$ possible histories. The probability of a complete history is the cumulative distribution function (CDF) of a trivariate normal distribution. To calculate the normal CDFs, we use the GHK smooth recursive simulator (Geweke, 1989; Hajivassiliou, 1990; and Keane, 1994).

form nonworking to full-time employment. To formally assess the role of part-time we compare the probabilities of full-time and part-time employment for individuals who have moved from non-working to part-time jobs. This comparison should indicate whether part-time jobs are stepping stones to full-time employment and, if so, what are the categories of individuals more likely to experience this transitions.

Figures 1 to 4 compare the probabilities of working full-time and part-time conditional on not working in wave 1 and gradually longer periods of part-time employment. Following one non-working year, the probability of working full-time is larger for all ages and categories of education (figure 1). Part-time represents a stepping stone for young women with high education and is more an absorbing state for older and lower educated women. Conditional on having worked part-time for one year, young highly educated women are just as likely to move to full-time jobs as they are to remain in the part-time jobs (figure 2). The probability of remaining in a part-time job is higher for older women with high education and for women of all ages with medium and low education. Longer part-time spells lower the probability of moving to a full-time job for all ages and categories of education (figures 3 and 4).

The birth of a child represents one of the strongest determinants of changes in the level of labor market involvement. Following birth, the time costs of child care may increase the attractiveness of part-time employment. The coefficient estimates in table 4 showed that having a child older than 3 increases the utility of part-time employment. We investigate the role of part-time during the period following birth by comparing full-time and part-time probabilities conditioning on a child being born in wave 2 and non-employment in wave 2. The state in the first wave is alternatively assumed full-time, part-time, and non-employment. Figures 5 to 7 plot the age profiles conditional on full-time employment in wave 1 and increasingly longer periods of unemployment following birth. Figure 8 assumes non-employment in wave 1 and compares full-time and part-time probabilities following 3 more non-working years. Finally, figures 9 to 11 condition on part-time in wave 1 and increasingly longer periods of non-employment following birth.

The state of labor market involvement to which a women returns after birth strongly depends on the state occupied before birth. If employed full-time before birth, full-time remains the more important destination regardless of the length of time spent out of the market, age or education (figures 5 to 7). Women who worked part-time before birth are more likely to return to part-time jobs, for all categories of education and ages (figures 9 to 11). The difference is higher for lower educated women. If not employed before birth, women with higher education are just as likely to start full-time or part-time jobs, women with lower levels of education have a higher probability of starting part-time jobs (figure 8).

5.3 Direct and indirect effects

The goal of the empirical analysis is threefold: evaluate the direct and indirect effects in each wave following the child birth; analyze how the direct effect changes with child's age; analyze how the indirect effect changes with time out of the labor market. Direct and indirect effects, as defined in the previous section, are represented as distances between high posterior density intervals of age profiles for the appropriate conditional probabilities. The change in age category in wave 5 and the simulation scenario in which age is held constant are used to evaluate the change in the direct effect with the child's age and the change in the indirect effect with the number of non-working years.

There is no indirect effect in wave 2, as no time out of the market has yet been taken. Conditional on working full-time in wave 1, the difference between the age profiles of working full-time and non-working represents the direct affect of having a child in wave 2 (figure 12). The direct effect is smaller for women with higher education levels. Opportunity costs of taking time out of the labor market are higher for women with higher education, fewer drop out of full-time employment for longer periods of time.

In waves 3 and 4, the direct effect measures the effect of a child age 0-2 on full-time probability, conditional on complete full-time history following birth. The distance between the uppermost two HPD intervals gives the age profile of the direct effect (figures 13 and 14). The indirect effect measures the difference in full-time probability given by a nonworking spell following birth - the distance between the bottom two HPD intervals. In both waves the direct effect is smaller than the indirect effect. The direct effect is larger for lower levels of education. Lower levels of education reduce the value of the latent variable and, due to the nonlinearity of the normal CDF, allow for larger effects of children.

How does the indirect effect changes with the length of the non-working time? A comparison of waves 3 and 4 indicates the indirect effect is larger for longer nonworking spells following birth. An extension of this comparison to wave 5 is hampered by the fact that the age category of the child changes in this wave. We use a simulation scenario in which the age category is held constant (figure 15) to overcome this problem. Holding age category constant, the indirect effect further increases with the time spent out of the labor market.

The change in the age category also allows us to assess how the direct effect changes with child's age. Again a comparison between waves 4 and 5 would be inappropriate. In addition to the change in age, the direct effects are different because they are calculated for different post-birth work histories. One extra year worked full-time increases the probability of working full-time in the next period, thus blurring the effect of age. The simulation scenario in which age category is held constant provides again the solution. A comparison of figures 14 and 15 allows inference on the effect of age holding post-birth work history constant. The direct effect unambiguously declines with the age of the child. In wave 5, with a child age 3-5, the direct effect all but disappears, holding age constant, the direct effect is significant for all. The relationship is robust across levels of education and age.

6 Conclusions

Children affect the after-birth labor force participation of women in two ways. Directly, the time spent in child-care reduces the labor market effort. This channel encompasses, for example, diminished physical capacity during the period surrounding birth, time-intensive child care, and availability of (affordable) day care. The time spent out of the labor market while on maternity leave alters women's participation experience and, thus, indirectly affects subsequent participation behavior. If labor force participation depends on experience and job seniority, interruptions will affect future labor market participation.

This paper proposes a model that disentangles the direct and indirect effect of children on women's labor force participation, and evaluates their relative importance. Participation decisions for three levels of labor market involvement - employed full-time, employed part-time, not employed - are represented by a multivariate probit model with a general correlation structure. The model allows for a high degree of flexibility in modeling the dependence of sequential decisions. The estimation is performed using Markov chain Monte Carlo methods.

Age has near-linear effects on the utilities associated with the three levels of labor market involvement. Younger women are more likely to work full-time. Higher education raises the utility of working full-time and lowers the utilities associate with part-time work and no work. Spouse's wage has a negative effect on the utility of a full-time job and positive effects on the utility of part-time and non-working. Spouse's participation and wage have opposite signs on utilities associated with all three states. The utility of working full-time increases for low levels of spouse's wage and falls bellow the level corresponding to a non-working husband as the wage increases. The effects on part time and non-working are reversed. The presence of children reduce the utility of working full-time, the effect is smaller for older children. At the same time children increase the utility of not working. The effect on the utility of working part-time is the most interesting. Very young children reduce the utility of working part-time. Older children make part-time more desirable. The maximum is attained for school-age children. It seems that women prefer to take part-time jobs when children go to school. This is consistent with our expectations given the lack of after-school care and the structure of the school day.

Consistent with the existing literature, we found that the level of labor market involvement is strongly persistent. Part-time work represents a bridge to full-time employment only for young, highly educated women. Following birth, women are likely to return to the level of labor market involvement prevailing pre birth. In general, part-time is more attractive to women with lower level of education.

The indirect effect of children, trough time out of the labor market, is stronger than the direct effect. The indirect effect grows with the length of the interruption and is larger for women with higher levels of education. We found a substantial direct effect of having children. In line with previous results, we found that the direct effect rapidly declines as the age of the child increases. The direct effect is larger for women with lower levels of education.

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Appendix

Define

$$B_{it}^{ft} = (0,\infty) \times (-\infty,0] \times (-\infty,0]$$
$$B_{it}^{pt} = (-\infty,0] \times (0,\infty) \times (-\infty,0]$$
$$B_{it}^{nw} = (-\infty,0] \times (-\infty,0] \times (0,\infty)$$

Every time period, the set of possible values that form Z_{it} is given by

$$B_{it} = B_{it}^{ft} \cup B_{it}^{pt} \cup B_{it}^{nw}$$

For individual i, the set of all feasible values of Z_i is $B_i = B_{i1} \times B_{i2} \times ... \times B_{iT}$

Using Bayes formula, the joint posterior distribution of the parameters, conditional on data, is

$$\pi(\beta,\sigma|y) \propto \pi(\beta,\sigma)\, pr(y|\beta,\Sigma) \qquad\qquad \beta \in R^k, \sigma \in C$$

where $\pi(\beta,\sigma)$ is the prior distribution of β and σ, and $pr(y|\beta,\Sigma) = \prod_i pr(y_i|\beta,\Sigma)$ is the likelihood function. C is a convex solid body in the hypercube $[-1,1]$ (Rousseeuw and Molenberghs, 1994). The shape of C is given by the following two conditions:

1. Each correlation coefficient lies in the interval $[-1,1]$.

2. The correlation matrix Σ is positive definite. Since Σ is symmetric, this condition reduces to $\det(\Sigma) > 0$.

The method proposed by Chib and Greenberg (1998) uses the same approach as data augmentation algorithm of Tanner and Wong (1987). Instead of using the posterior distribution in this form, we use the joint posterior of both parameters and latent variables, $\pi(\beta,\sigma,Z_1,...,Z_n|y)$.

$$\pi(\beta,\sigma,Z|y) \propto \pi(\beta,\sigma)\, f(Z|\beta,\Sigma)\, pr(y|Z,\beta,\sigma)$$

Conditional on Z_i, we have $pr(y_i|Z_i,\beta,\sigma) = I(Z_i \in B_i)$. The posterior distribution becomes

$$\pi(\beta,\sigma,Z|y) \propto \pi(\beta,\sigma) \prod_i f(Z_i|\beta,\Sigma)\, I(Z_i \in B_i)$$

where

$$f\left(Z_i|\beta,\Sigma\right) \propto |\Sigma|^{-\frac{1}{2}} \exp\left\{-\frac{1}{2}\left(Z_i - X_i\beta\right)' \Sigma^{-1}\left(Z_i - X_i\beta\right)\right\} I\left(\sigma \in C\right)$$

Regarding the latent variable as a parameter, we sample from the conditional distributions:

- Conditional distribution of Z_i

$$[Z_i|y_i,\beta,\Sigma] \propto \phi_T\left(Z_i|X_i\beta,\Sigma\right)\prod_i \left\{I\left(z_{it}>0\right)I\left(y_{it}=1\right)+I\left(z_{it}\leq 0\right)I\left(y_{it}=0\right)\right\}$$

To draw from a truncated normal distribution, we used the method proposed by Geweke (1991), which consists of running a Gibbs sub-chain with T steps within the main Gibbs sampler cycle.

- Conditional Distribution of β

We assume prior independence between β and σ. The prior distribution of β is a k-variate normal distribution $\pi\left(\beta\right) = \phi_k\left(\beta|\beta_0, B_0^{-1}\right)$. Conditional distribution is

$$[\beta|Z,\Sigma] \sim N_k\left(\beta|\hat{\beta}, B^{-1}\right)$$

where

$$\hat{\beta} = B^{-1}\left(B_0\beta_0 + \sum_{i=1}^{n} X_i'\Sigma^{-1}Z_i\right)$$

and

$$B = B_0 + \sum_{i=1}^{n} X_i'\Sigma^{-1}X_i$$

- Conditional Distribution of σ

$$\begin{aligned}
\pi\left(\sigma|Z,\beta\right) &\propto \pi\left(\sigma\right) f\left(Z|\beta,\Sigma\right) \\
f\left(Z|\beta,\Sigma\right) &\propto |\Sigma|^{-\frac{n}{2}} \exp\left\{-\frac{1}{2} tr\left(Z^* - \Delta\right)' \Sigma^{-1}\left(Z^* - \Delta\right)\right\} I\left(\sigma \in C\right)
\end{aligned}$$

where $Z^* = (Z_1, ..., Z_n)$ and $\Delta = (X_1\beta, ..., X_n\beta)$. Prior distribution of σ is a normal distribution truncated at C

$$\pi(\sigma) \propto \phi_p\left(\sigma|\sigma_0, G_0^{-1}\right) \qquad\qquad \sigma \in C$$

where p is the number of free parameters in the correlation matrix. To draw from this distribution we use a MH step within the Gibbs sampler.

Convergence of the chain is assessed using the method proposed by Gelman and Rubin (1992) with the modified correction factor proposed by Brooks and Gelman (1998). One preliminary run of 15000 iterations, with OLS coefficients as starting values, was used to construct starting values for three independent chains. The starting values were extreme values chosen form the posterior distribution of the coefficients. The three independent chains, each with 15000 iterations and the initial run, were used to compute the scale reduction factor. We also evaluated the convergence criterion proposed by Geweke(1992) based on a single chain, which uses spectral density estimates of the series. Both criteria indicated that the chain converges fast to the stationary distribution.

We follow Chib and Greenberg (1998) in setting the parameters of the algorithm. The prior distribution of β is multivariate normal with a mean vector of 0 and a variance matrix of 100 times the identity matrix. The prior distribution of the elements of the correlation matrix is multivariate normal with a mean vector of 0 and a variance matrix equal to 10 times the identity matrix. The proposal density used to generate candidate values in the MH step is $q\left(\phi|\sigma_i^k\right) = s * g\left(\phi - \sigma_i^k\right)$ where g is the standard normal distribution and s is the step size. We use a step size $s = 1/\sqrt{N}$.

Wave		Age	Med. Educ	Low Educ	Log monthly non-wage HH Inc.	Log monthly spouse's income from work	Fraction with working spouse	No. of kids [0,3)	No. of kids [3,6)	No. of kids [6,17)	No. of kids [17,∞)	Fraction working FT	Fraction working PT	Fraction not working
W1	mean	41.90	.57	.25	5.70	5.95	.75	.08	.14	.61	.41	.37	.16	.47
(1994)	stdev	10.16			2.37	3.44		.3	.37	.87	.73			
	min	25			0	0		0	0	0	0			
	max	61			11.96	10.09		2	2	5	5			
W2	mean	42.90	.57	.25	5.80	5.86	.74	.07	.13	.61	.41	.35	.17	.48
(1995)	stdev	10.16			2.35	3.50		.27	.38	.87	.69			
	min	26			0	0		0	0	0	0			
	max	62			11.99	10.06		2	3	5	5			
W 3	mean	43.90	.57	.25	5.75	5.60	.71	.07	.12	.60	.41	.33	.17	.50
(1996)	stdev	10.16			2.45	3.65		.26	.35	.86	.68			
	min	27			0	0		0	0	0	0			
	max	63			12.16	9.39		2	2	4	4			
W4	mean	44.90	.57	.25	5.76	5.42	.68	.06	.11	.58	.44	.32	.18	.50
(1997)	stdev	10.16			2.52	3.74		.24	.34	.84	.69			
	min	28			0	0		0	0	0	0			
	max	64			12.20	10.31		2	2	4	5			
W5	mean	45.90	.57	.25	5.79	5.32	.67	.06	.10	.56	.45	.32	.17	.53
(1998)	stdev	10.16			2.58	3.78		.24	.32	.83	.70			
	min	29			0	0		0	0	0	0			
	max	65			12.13	9.39		2	2	5	5			

Table 1. Characteristics of the sample by wave. 'Med. Educ.' indicates medium education (ISCED 3). 'Low Educ.' indicates low education (ISCED 0-2). High education (ISCED 5-7) is omitted.

	No. of	Age 25 - 35			No. of	Age 35 - 45			No. of	Age 45 - 55			No. of	Age 55 - 65		
	Obs.	FT	PT	NW	Obs.	FT	PT	NW	Obs.	FT	PT	NW	Obs.	FT	PT	NW
High Education																
No children	140	.6357	.1571	.2071	107	.8131	.0935	.0935	198	.6818	.1212	.1970	207	.3333	.0821	.5845
At least one child [0,3)	103	.0583	.0971	.8447	41	.1951	.0976	.7073	-	-	-	-	-	-	-	-
At least one child [3,6)	144	.3264	.1944	.4792	128	.2656	.2109	.5234	1	1.0000	.0000	.0000	-	-	-	-
At least one child [6,17)	238	.5420	.1555	.3025	733	.5648	.1896	.2456	106	.6038	.1509	.2453	2	.0000	.0000	1.0000
At least one child [17,.)	3	.6667	.0000	.3333	326	.7209	.0767	.2025	277	.6751	.1372	.1877	84	.3929	.0357	.5714
Medium Education																
No children	449	.7862	.0535	.1604	273	.6410	.1575	.2015	732	.4713	.2036	.3251	1021	.1939	.0872	.7189
At least one child [0,3)	472	.0339	.0530	.9131	90	.0667	.0333	.9000	3	.3333	.0000	.6667	-	-	-	-
At least one child [3,6)	633	.1090	.1769	.7141	252	.0913	.1865	.7222	15	.0000	.2667	.7333	-	-	-	-
At least one child [6,17)	888	.2962	.1745	.5293	1639	.2837	.2465	.4698	319	.1787	.3354	.4859	12	.3333	.1667	.5000
At least one child [17,.)	5	.8000	.0000	.2000	770	.3974	.2416	.3610	853	.3025	.2532	.4443	313	.1310	.1214	.7476
Low Education																
No children	67	.6716	.1045	.2239	68	.3971	.0882	.5147	320	.3594	.1438	.4969	559	.1181	.0769	.8050
At least one child [0,3)	95	.0947	.0632	.8421	30	.0000	.0000	1.0000	3	.0000	.0000	1.0000	-	-	-	-
At least one child [3,6)	169	.1479	.1124	.7396	72	.1250	.1667	.7083	2	.0000	.0000	1.0000	-	-	-	-
At least one child [6,17)	321	.1495	.1745	.6760	537	.2533	.1825	.5642	213	.2207	.1268	.6526	29	.0690	.2414	.6897
At least one child [17,.)	4	.5000	.0000	.5000	423	.3452	.1631	.4917	613	.2316	.1827	.5856	433	.1132	.1848	.7021

Table 2. Mean incidence of full time work, part time work and non employment by education and family structure. Waves 1-5 combined. Low, medium and high education correspond to ISCED 0-2, ISCED 3, and ISCED 5-7, respectively.

LF Status		Wave 2			Total
		FT	PT	NW	
Wave 1	FT	779	50	126	955
	PT	48	288	76	412
	NW	87	95	1027	1209
Total		914	433	1229	2576

LF Status		Wave 3			Total
		FT	PT	NW	
Wave 2	FT	749	41	124	914
	PT	38	311	84	433
	NW	65	87	1077	1229
Total		852	439	1285	2576

LF Status		Wave 4			Total
		FT	PT	NW	
Wave 3	FT	707	53	92	852
	PT	39	314	86	439
	NW	82	86	1117	1285
Total		828	453	1295	2576

LF Status		Wave 5			Total
		FT	PT	NW	
Wave 4	FT	700	37	91	828
	PT	56	325	72	453
	NW	60	66	1169	1295
Total		816	428	1332	2576

LF Status		Wave 5			Total
		FT	PT	NW	
Wave 1	FT	639	70	246	955
	PT	69	216	127	412
	NW	108	142	959	1209
Total		816	428	1332	2576

Figure A. Wave by wave transition matrices between full time (FT), part time (PT), and non-employment (NW) states.

Full Time β_0	R	mean	NSE	popstd
constant	1.000544	6.4253	0.0236	2.5300
age	1.000479	-0.4199	0.0017	0.1904
age^2	1.000461	1.1140	0.0040	0.4600
age^3	1.000444	-0.1004	0.0003	0.0359
educ1	1.000222	-0.6903	0.0005	0.0785
educ2	1.000361	-0.8505	0.0008	0.0952
nwinc	1.000379	-0.0171	0.0001	0.0121
spwage	1.000770	-0.3521	0.0008	0.0601
sppart	1.000986	2.6586	0.0068	0.4735
kids03	1.001367	-1.6203	0.0023	0.1797
kids36	1.000371	-0.5797	0.0008	0.0909
kids617	1.000479	-0.3463	0.0004	0.0433
kids>17	1.001547	-0.0835	0.0008	0.0440

Full Time β_0	R	mean	NSE	popstd
constant	1.000394	5.9918	0.0153	1.8529
age	1.000562	-0.4075	0.0013	0.1323
age^2	1.000726	1.1308	0.0035	0.3054
age^3	1.000912	-0.1058	0.0003	0.0229
educ1	1.000110	-0.7295	0.0003	0.0524
educ2	1.000170	-0.9361	0.0003	0.0634
nwinc	1.001037	-0.0063	0.0001	0.0068
spwage	1.000454	-0.2882	0.0003	0.0306
sppart	1.000377	2.2040	0.0021	0.2393
kids03	1.001237	-1.3086	0.0011	0.0908
kids36	1.001041	-0.8425	0.0009	0.0603
kids617	1.000699	-0.3963	0.0003	0.0280
kids>17	1.000047	-0.1410	0.0001	0.0286

Table 3. Results from the posterior density draws. Full time parameters. Educ1, educ2, and educ3 correspond to low (ISCED 0-2), medium (ISCED 3) and highly educated (ISCED 5-7), respectively. The variables nwinc, spwage and sppart indicate household non labor income (logs), spouse's income from wages (logs) and a dummy indicator for spouse's participation. The 'kids' variables indicate the number of children in the various age groups.

Part time β_0	R	mean	NSE	popstd
constant	1.000902	-4.1925	0.0373	2.9101
age	1.000807	0.1457	0.0026	0.2167
age^2	1.000706	-0.2068	0.0058	0.5198
age^3	1.000633	0.0057	0.0004	0.0403
educ1	1.000020	0.1964	0.0004	0.0903
educ2	1.000198	0.0539	0.0007	0.1084
nwinc	1.000312	0.0283	0.0001	0.0142
spwage	1.000344	0.1558	0.0006	0.0771
sppart	1.000385	-1.1619	0.0048	0.6167
kids03	1.001303	-0.5874	0.0025	0.1534
kids36	1.000277	0.0308	0.0007	0.0936
kids617	1.000751	0.0444	0.0005	0.0454
kids>17	1.000747	0.0370	0.0006	0.0484

Part time β_1	R	mean	NSE	popstd
constant	1.000143	3.2490	0.0112	1.9300
age	1.000085	-0.3707	0.0006	0.1372
age^2	1.000073	0.9930	0.0013	0.3156
age^3	1.000080	-0.0856	0.0001	0.0235
educ1	1.000277	0.1871	0.0003	0.0536
educ2	1.000032	0.1037	0.0001	0.0648
nwinc	1.000765	0.0108	0.0001	0.0074
spwage	1.000795	0.1912	0.0005	0.0397
sppart	1.000732	-1.4752	0.0037	0.3168
kids03	1.002922	-0.6561	0.0018	0.0875
kids36	1.000631	0.0258	0.0006	0.0537
kids617	1.000372	0.0555	0.0002	0.0276
kids>17	1.000155	0.0186	0.0001	0.0301

Table 4. Results from the posterior density draws. Part time parameters. Educ1, educ2, and educ3 correspond to low (ISCED 0-2), medium (ISCED 3) and highly educated (ISCED 5-7), respectively. The variables nwinc, spwage and sppart indicate household non labor income (logs), spouse's income from wages (logs) and a dummy indicator for spouse's participation. The 'kids' variables indicate the number of children in the various age groups.

Not-working β_0	R	mean	NSE	popstd
constant	1.000805	-4.1852	0.0301	2.4185
age	1.000888	0.2853	0.0024	0.1819
age^2	1.000938	-0.8831	0.0060	0.4390
age^3	1.000972	0.0886	0.0005	0.0342
educ1	1.000203	0.5431	0.0005	0.0782
educ2	1.000250	0.7811	0.0007	0.0925
nwinc	1.000156	-0.0056	0.0001	0.0115
spwage	1.000229	0.2068	0.0004	0.0568
sppart	1.000251	-1.6081	0.0033	0.4496
kids03	1.001568	1.6230	0.0022	0.1280
kids36	1.000694	0.5091	0.0009	0.0789
kids617	1.000167	0.2926	0.0002	0.0398
kids>17	1.000411	0.0605	0.0004	0.0416

Not-working β_1	R	mean	NSE	popstd
constant	1.000547	-7.5203	0.0154	1.7870
age	1.000732	0.5275	0.0014	0.1272
age^2	1.000902	-1.4703	0.0036	0.2926
age^3	1.001073	0.1356	0.0003	0.0218
educ1	1.000608	0.5781	0.0006	0.0533
educ2	1.000429	0.7896	0.0006	0.0631
nwinc	1.001075	-0.0068	0.0001	0.0064
spwage	1.001221	0.1416	0.0005	0.0303
sppart	1.001331	-1.1150	0.0039	0.2385
kids03	1.000751	1.5051	0.0009	0.0760
kids36	1.001634	0.6897	0.0009	0.0506
kids617	1.001866	0.3182	0.0005	0.0267
kids>17	1.000250	0.1144	0.0002	0.0279

Table 5. Results from the posterior density draws. Non-work parameters. Educ1, educ2, and educ3 correspond to low (ISCED 0-2), medium (ISCED 3) and highly educated (ISCED 5-7), respectively. The variables nwinc, spwage and sppart indicate household non labor income (logs), spouse's income from wages (logs) and a dummy indicator for spouse's participation. The 'kids' variables indicate the number of children in the various age groups.

	FT94	FT95	FT96	FT97	FT98	PT94	PT95	PT96	PT97	PT98	NW94	NW95	NW96	NW97	NW98
FT94	1	0.5708	0.5614	0.5111	0.4998	-0.1688	-0.1603	-0.1797	-0.1441	-0.1707	-0.4791	-0.4178	-0.3939	-0.3525	-0.3290
FT95		1	0.5917	0.5421	0.5340	-0.1506	-0.1780	-0.1850	-0.1496	-0.1786	-0.4438	-0.4657	-0.4175	-0.3759	-0.3544
FT96			1	0.5724	0.5604	-0.1348	-0.1491	-0.1788	-0.1308	-0.1557	-0.4474	-0.4475	-0.4748	-0.4188	-0.3963
FT97				1	0.5555	-0.1464	-0.1567	-0.1799	-0.1614	-0.1684	-0.3897	-0.3939	-0.4025	-0.4257	-0.3805
FT98					1	-0.1072	-0.1178	-0.1354	-0.1022	-0.1475	-0.4081	-0.4167	-0.4252	-0.4247	-0.4409
PT94						1	0.4604	0.4378	0.4182	0.3908	-0.2207	-0.2161	-0.2106	-0.2071	-0.2068
PT95							1	0.4918	0.4662	0.4406	-0.1885	-0.2626	-0.2399	-0.2372	-0.2368
PT96								1	0.4890	0.4645	-0.1529	-0.2080	-0.2626	-0.2340	-0.2387
PT97									1	0.4869	-0.1732	-0.2212	-0.2540	-0.3060	-0.2869
PT98										1	-0.1266	-0.1742	-0.2117	-0.2431	-0.2820
NW94											1	0.5709	0.5444	0.5015	0.4783
NW95												1	0.5880	0.5452	0.5247
NW96													1	0.5796	0.5613
NW97														1	0.5840
NW98															1

Table 6. Posterior means for the correlation coefficients. Wave 1 - 5 correspond to 1994 - 1998.
PT, FT, and NW indicate fullt time, part time and non-employment status, respectively.

Education	Age Group	Full Time Predicted	Full Time Observed	Part Time Predicted	Part Time Observed	Not-Working Predicted	Not-Working Observed
educ0	25-30	0.724	0.492	0.020	0.138	0.256	0.369
educ0	30-35	0.643	0.507	0.032	0.189	0.325	0.303
educ0	35-40	0.727	0.585	0.041	0.160	0.232	0.255
educ0	40-45	0.851	0.716	0.034	0.122	0.114	0.162
educ0	45-50	0.865	0.687	0.031	0.138	0.103	0.174
educ0	50-55	0.706	0.584	0.030	0.149	0.264	0.267
educ0	55+	0.225	0.210	0.016	0.060	0.759	0.730
educ1	25-30	0.364	0.365	0.038	0.115	0.598	0.520
educ1	30-35	0.296	0.317	0.055	0.199	0.649	0.484
educ1	35-40	0.371	0.330	0.075	0.212	0.553	0.458
educ1	40-45	0.448	0.386	0.089	0.291	0.463	0.323
educ1	45-50	0.474	0.359	0.080	0.232	0.446	0.409
educ1	50-55	0.204	0.314	0.047	0.171	0.749	0.514
educ1	55+	0.037	0.145	0.013	0.063	0.950	0.792
educ2	25-30	0.206	0.259	0.030	0.141	0.764	0.600
educ2	30-35	0.152	0.231	0.038	0.172	0.810	0.597
educ2	35-40	0.221	0.314	0.055	0.195	0.725	0.491
educ2	40-45	0.321	0.261	0.065	0.152	0.614	0.586
educ2	45-50	0.288	0.327	0.059	0.156	0.654	0.517
educ2	50-55	0.111	0.205	0.029	0.168	0.861	0.626
educ2	55+	0.017	0.094	0.007	0.113	0.976	0.793

Table 7. Mean fraction of women not working, working full time or working part time, for different age groups and education levels. The category educ0 indicates highly educated (ISCED5-7) educ1 indicates medium educated (ISCED 3) and educ2 indicates low educated (ISCED 0-2).

Figure 1. Comparing probability of full-time and part-time employment in wave 2 conditional on non-working in wave 1.

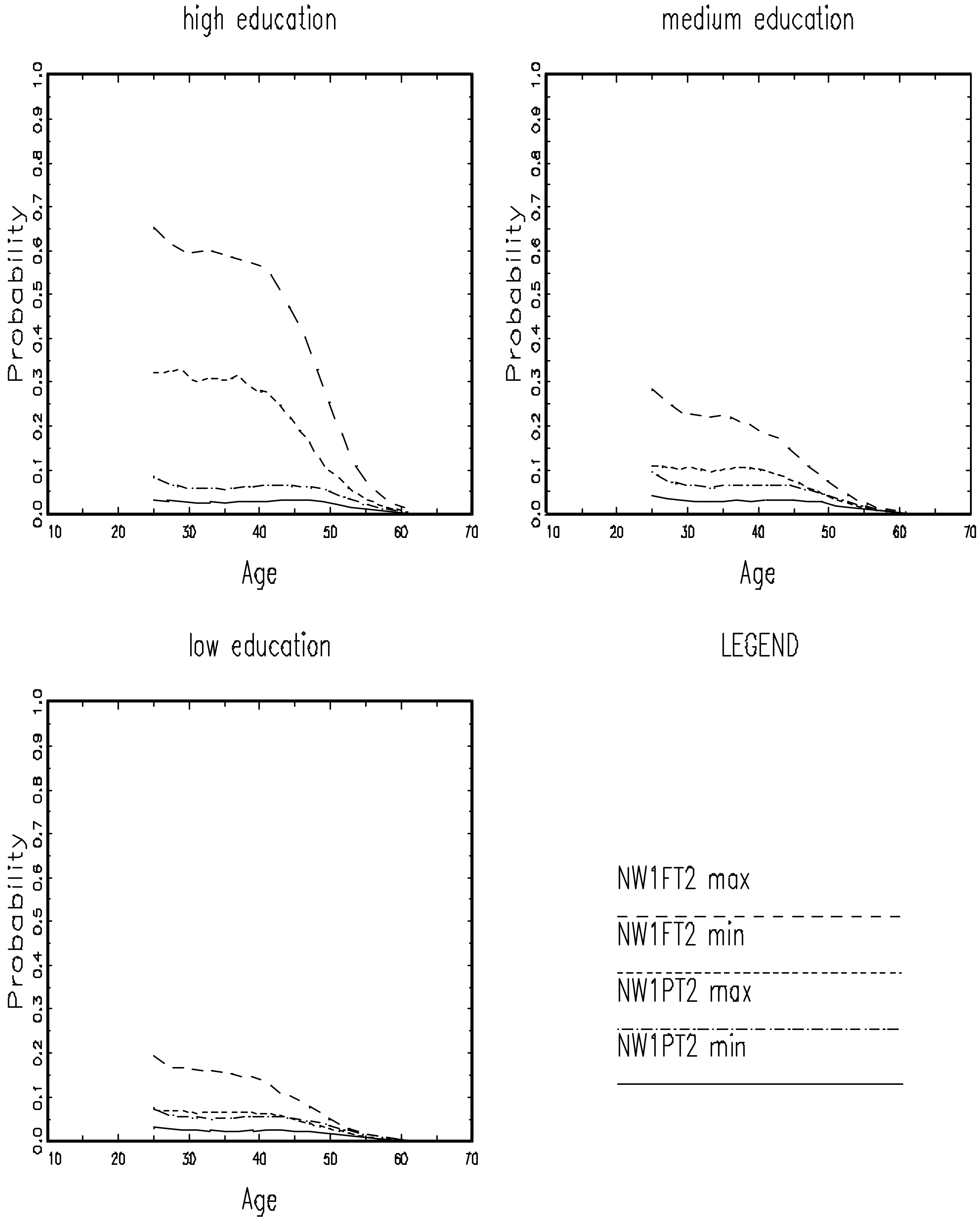

Figure 2. Comparing probability of full-time and part-time employment in wave 3 conditional on non-working in wave 1 and part-time in wave 2.

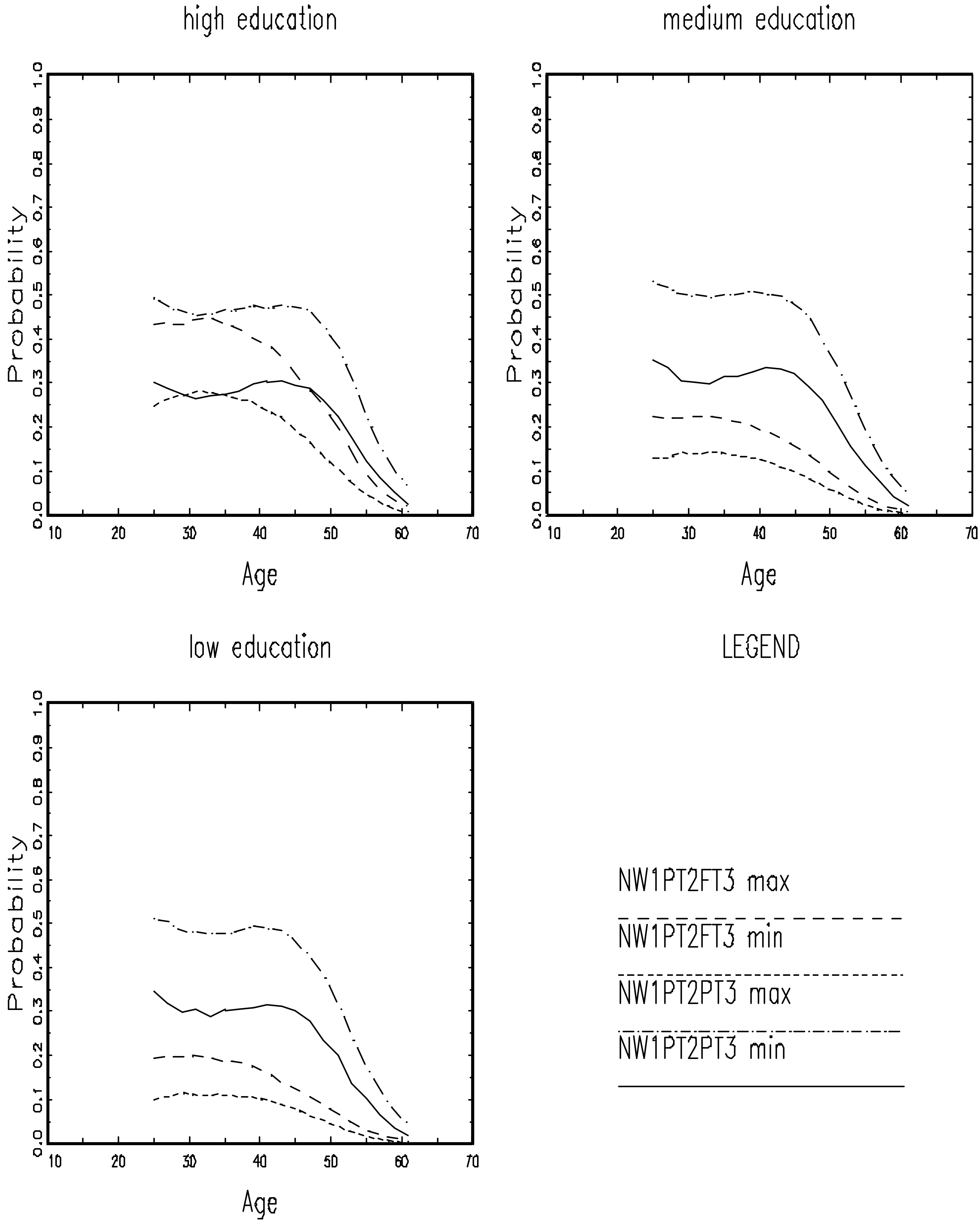

Figure 3. Comparing probability of full-time and part-time employment in wave 4 conditional on non-working in wave 1 and part-time in wave 2 and 3.

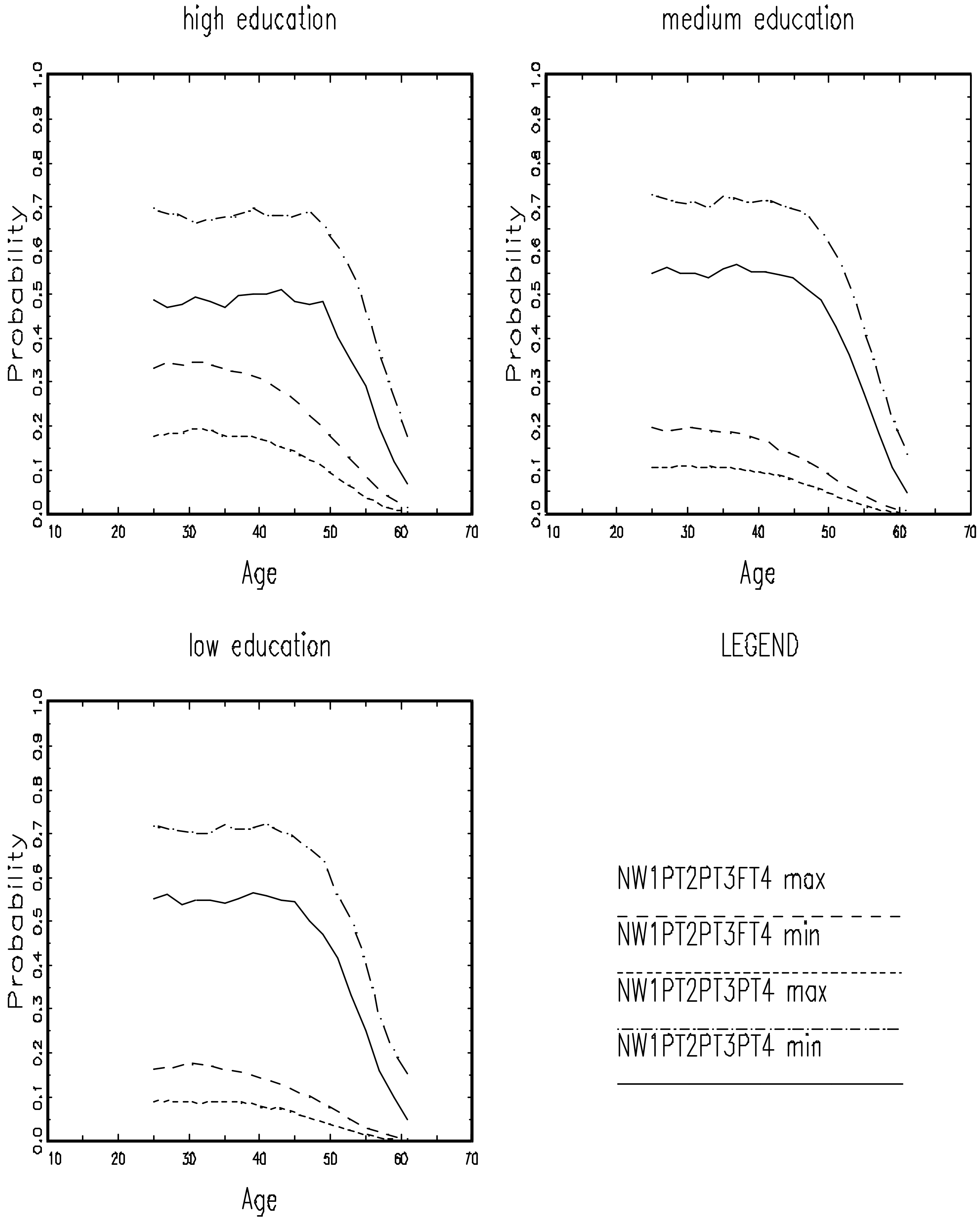

Figure 4. Comparing probability of full-time and part-time employment in wave 5 conditional on non-working in wave 1 and part-time in wave 2, 3 and 4.

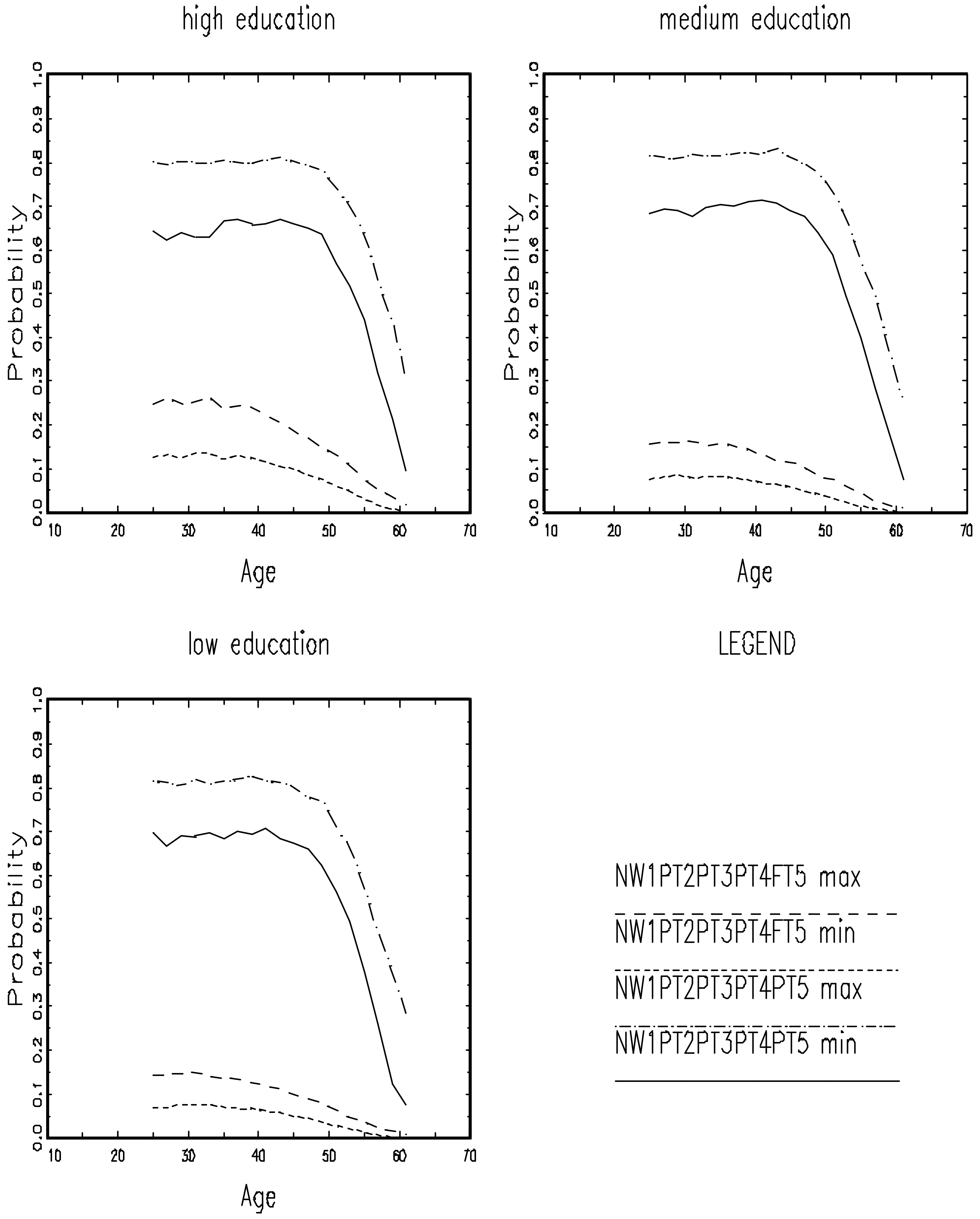

Figure 5. Comparing probability of full-time and part-time employment in wave 3. Probabilities are calculated conditional on full-time in wave 1, having a child 0-2 in wave 2, and non-work in wave 2.

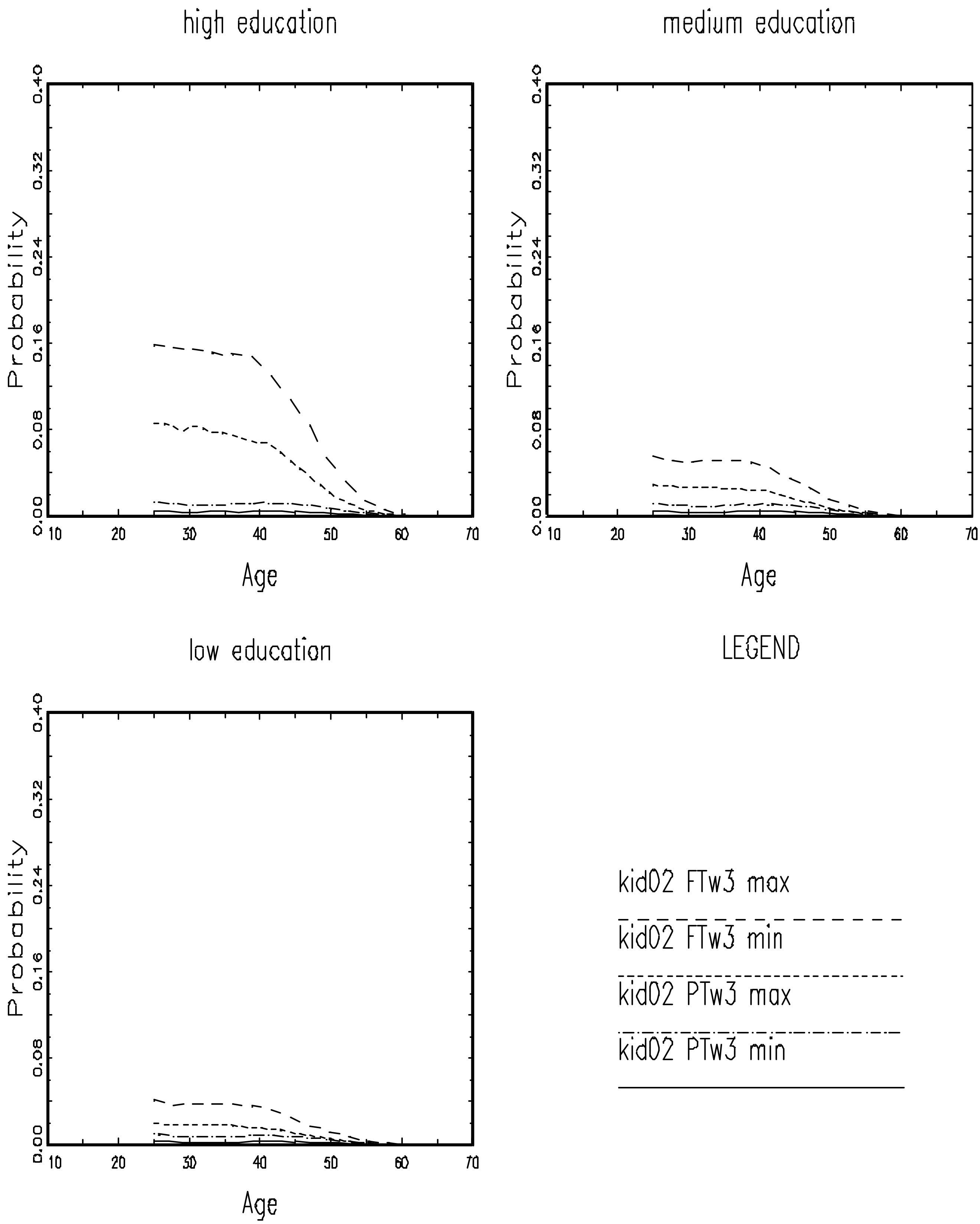

Figure 6. Comparing probability of full-time and part-time employment in wave 4 conditional on an extra year non-working in wave 3. Probabilities are calculated conditional on full-time in wave 1, having a child 0-2 in wave 2, and non-work in wave 2.

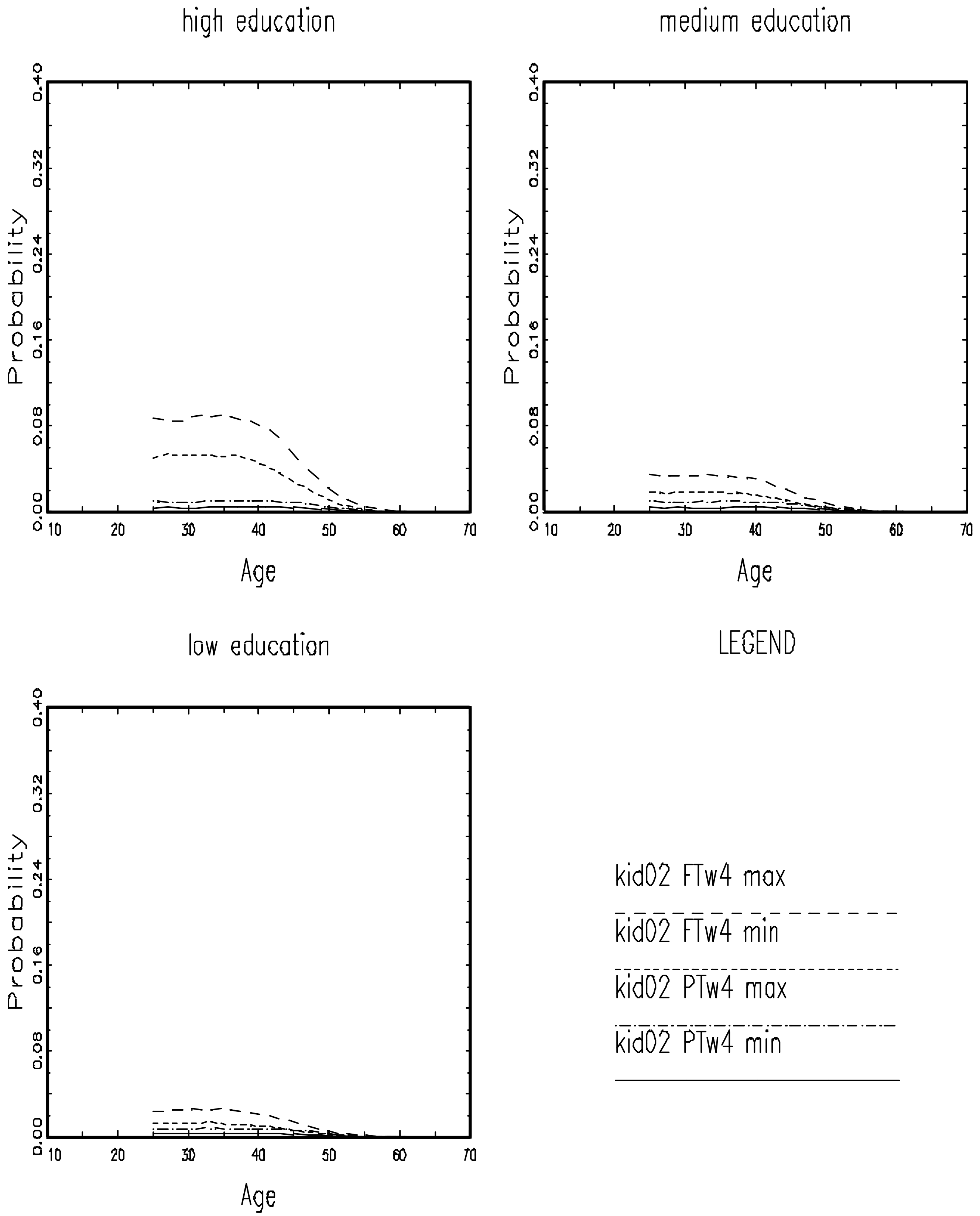

Figure 7. Comparing probability of full-time and part-time employment in wave 5 conditional on two extra years non-working in wave 3 and 4. The child is in catagory 3-5. Probabilities are calculated conditional on full-time in wave 1, having a child 0-2 in wave 2, and non-work in wave 2.

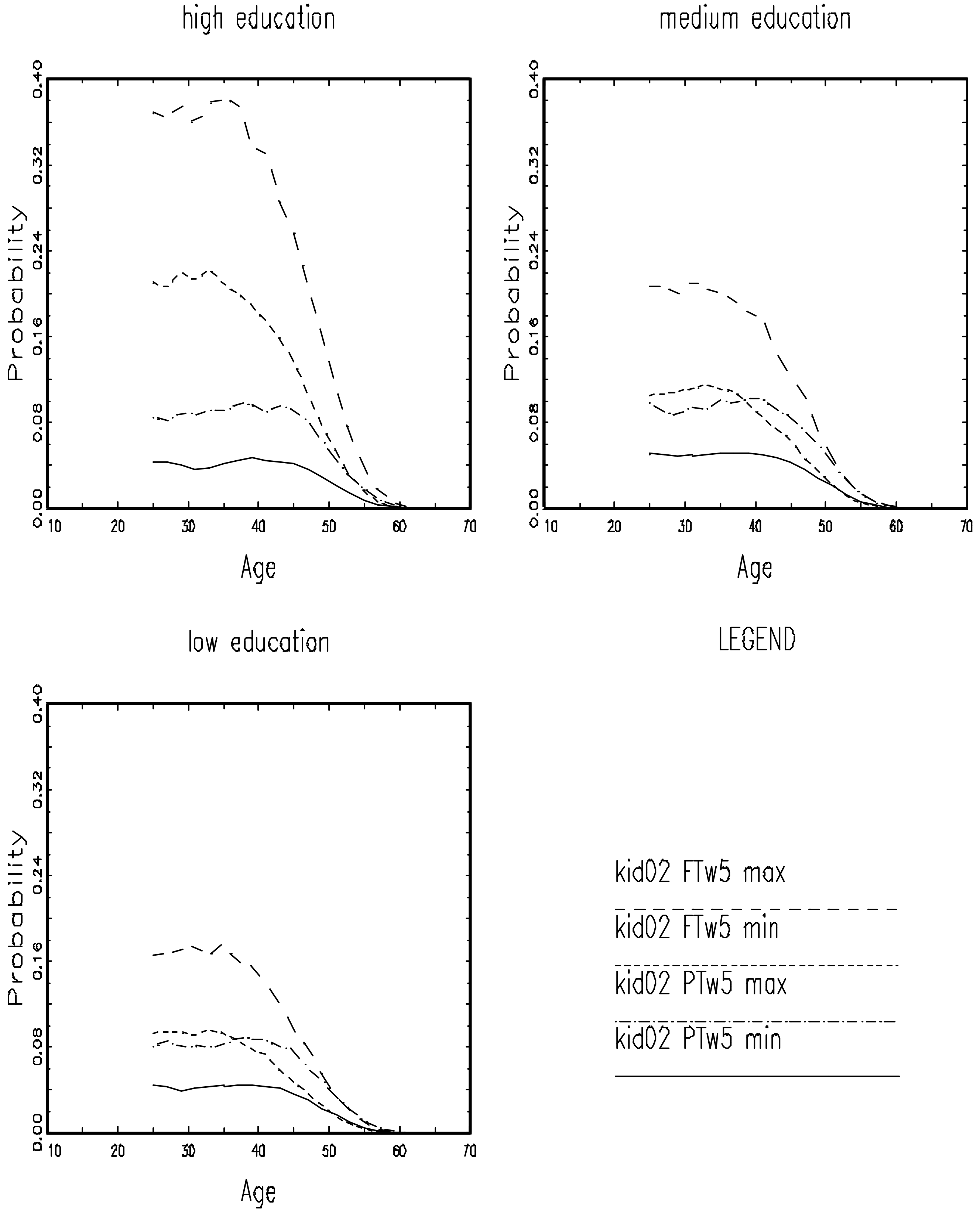

Figure 8. Comparing probability of full-time and part-time employment in wave 5 conditional on two extra years non-working in wave 3 and 4. The child is in catagory 3-5. Probabilities are calculated conditional on non-working in wave 1, having a child 0-2 in wave 2, and non-work in wave 2.

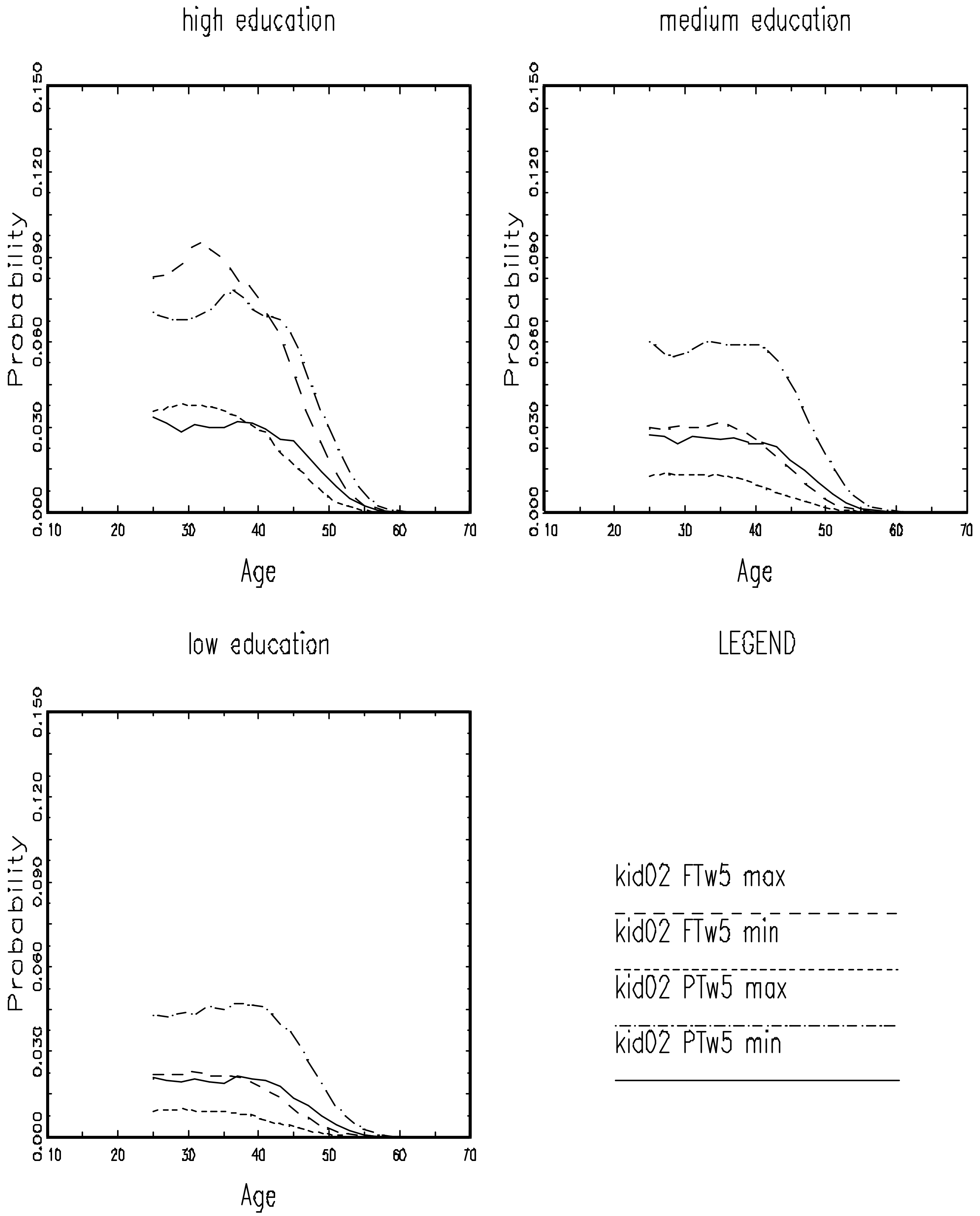

Figure 9. Comparing probability of full-time and part-time employment in wave 3. Probabilities are calculated conditional on part-time in wave 1, having a child 0-2 in wave 2, and non-work in wave 2.

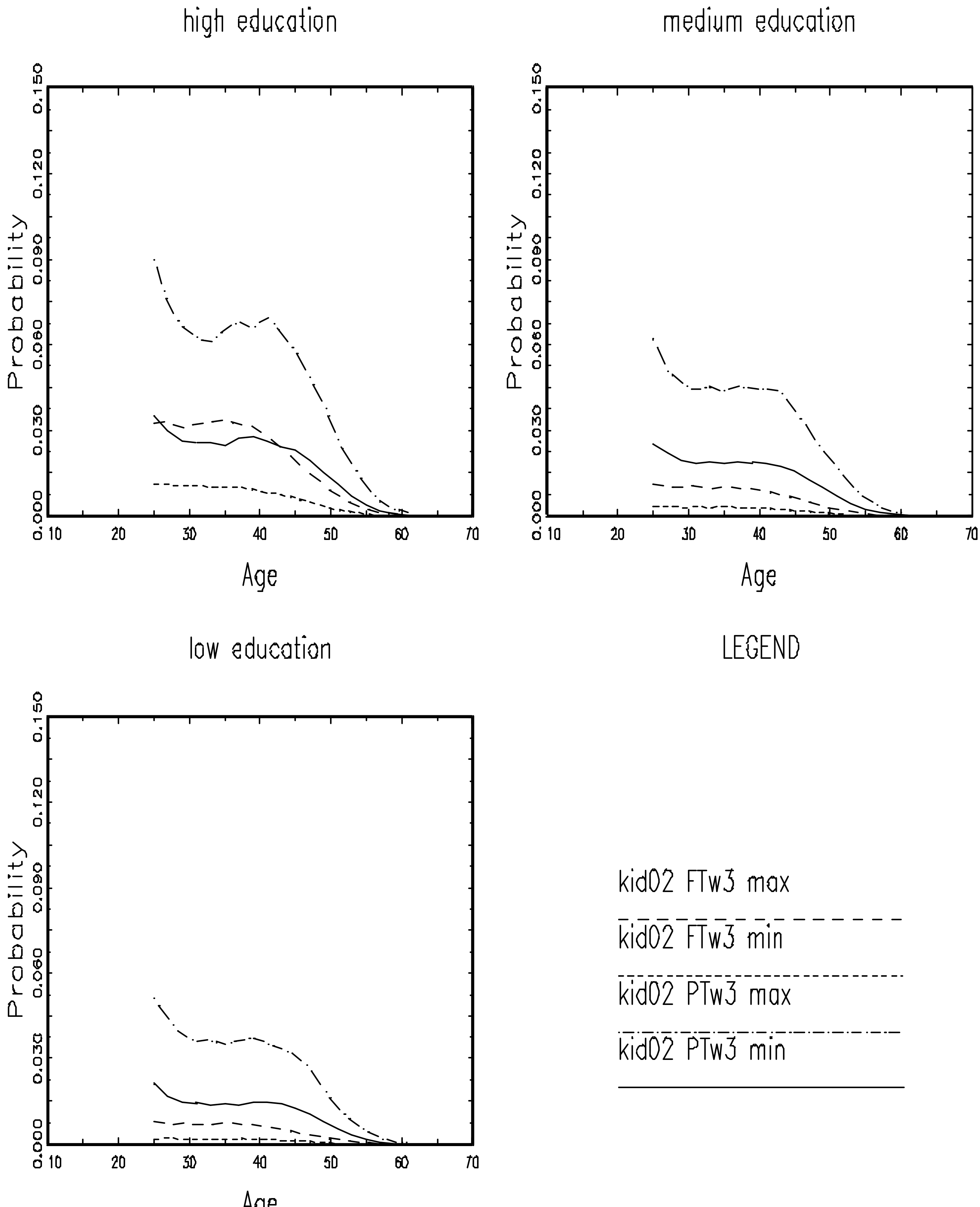

Figure 10. Comparing probability of full-time and part-time employment in wave 4 conditional on an extra year non-working in wave 3. Probabilities are calculated conditional on part-time in wave 1, having a child 0-2 in wave 2, and non-work in wave 2.

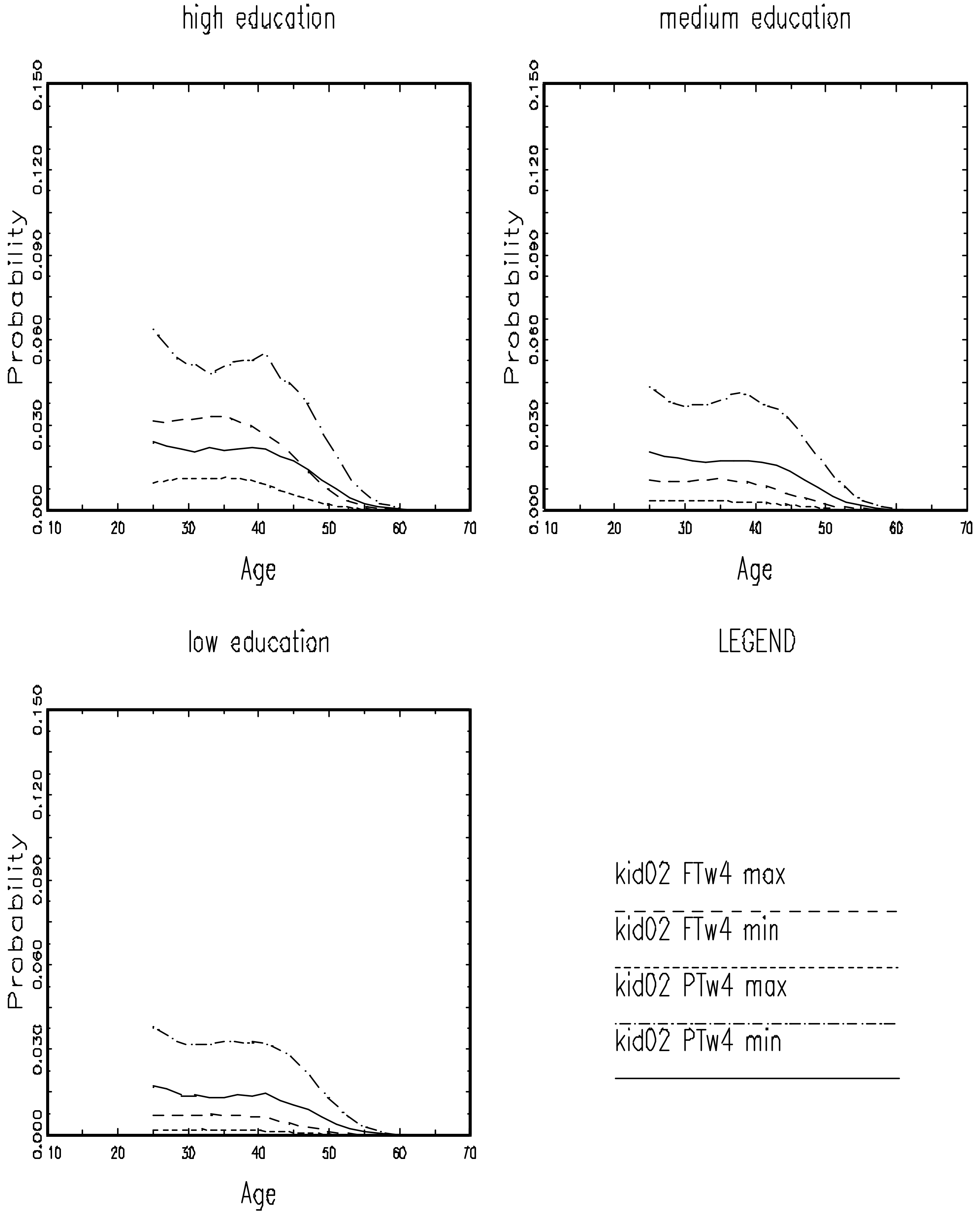

Figure 11. Comparing probability of full-time and part-time employment in wave 5 conditional on two extra years non-working in wave 3 and 4. The child is in age catagory 3-5. Probabilities are calculated conditional on part-time in wave 1, having a child 0-2 in wave 2, and non-work in wave 2.

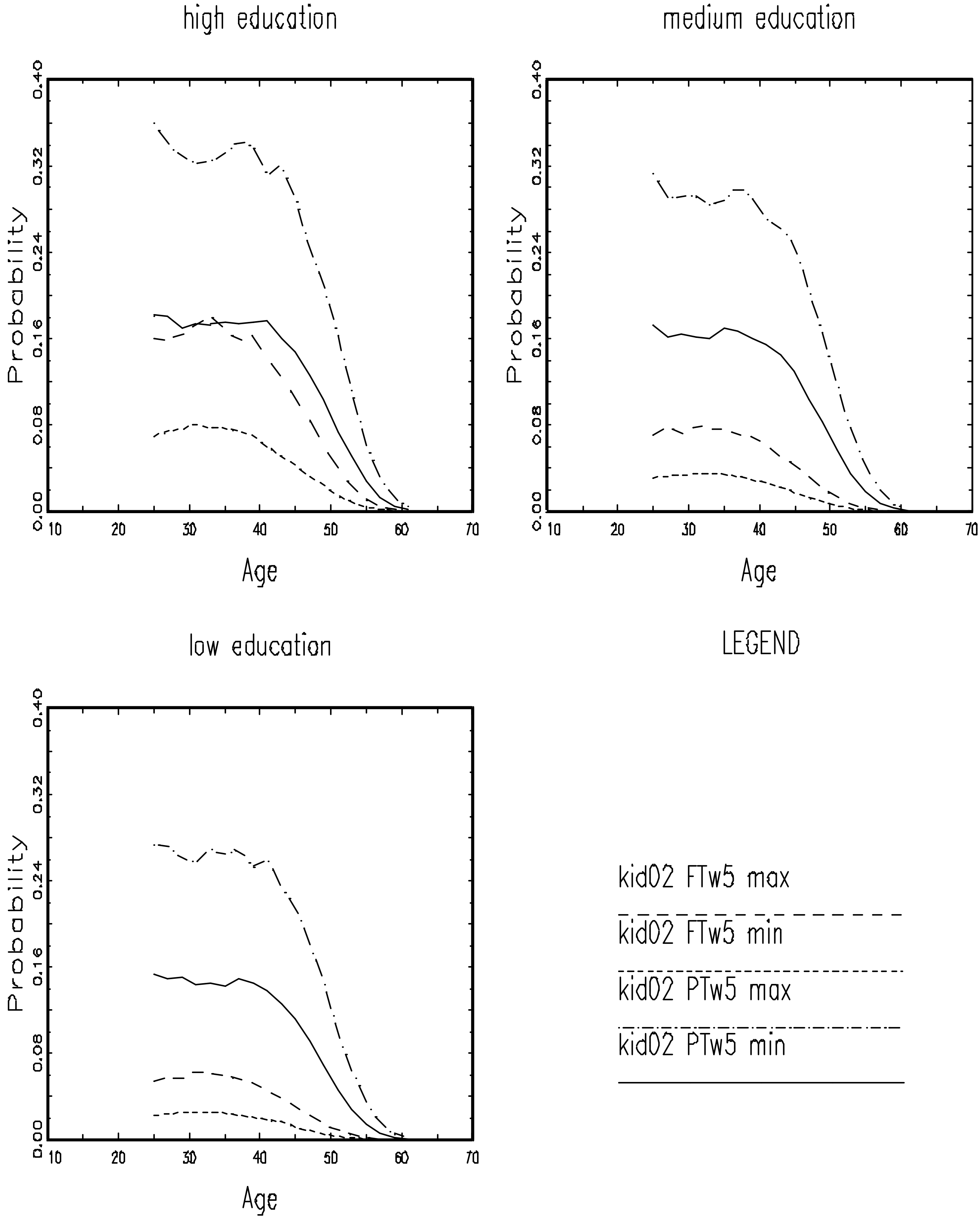

Figure 12. Direct effect in wave 2. Probabilities are calculated conditional on full-time employment in wave 1.

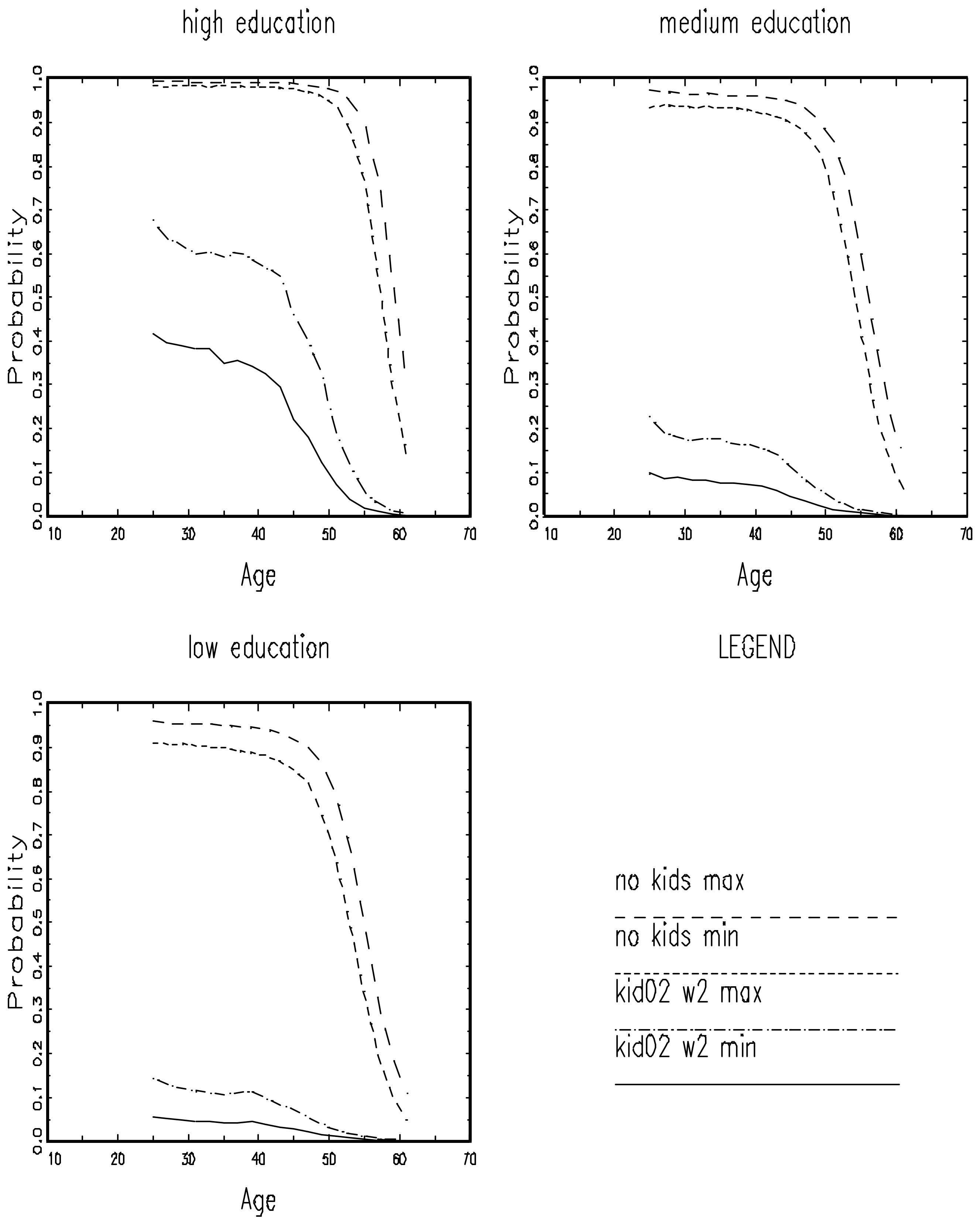

Figure 13. Direct and indirect effects in wave 3. Probabilities are calculated conditional on full-time employment in wave 1.

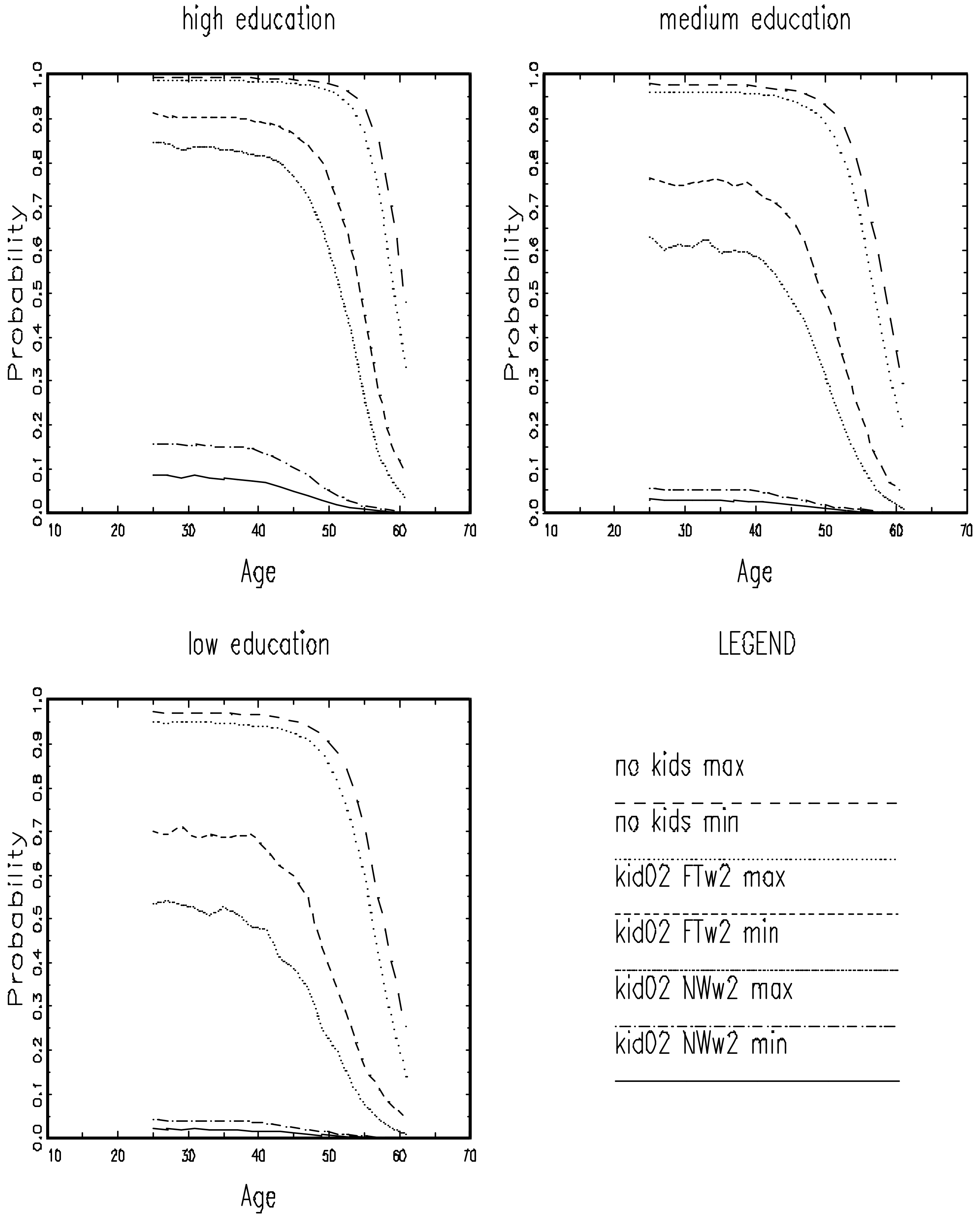

Figure 14. Direct and indirect effects in wave 4. Probabilities are calculated conditional on full-time employment in wave 1.

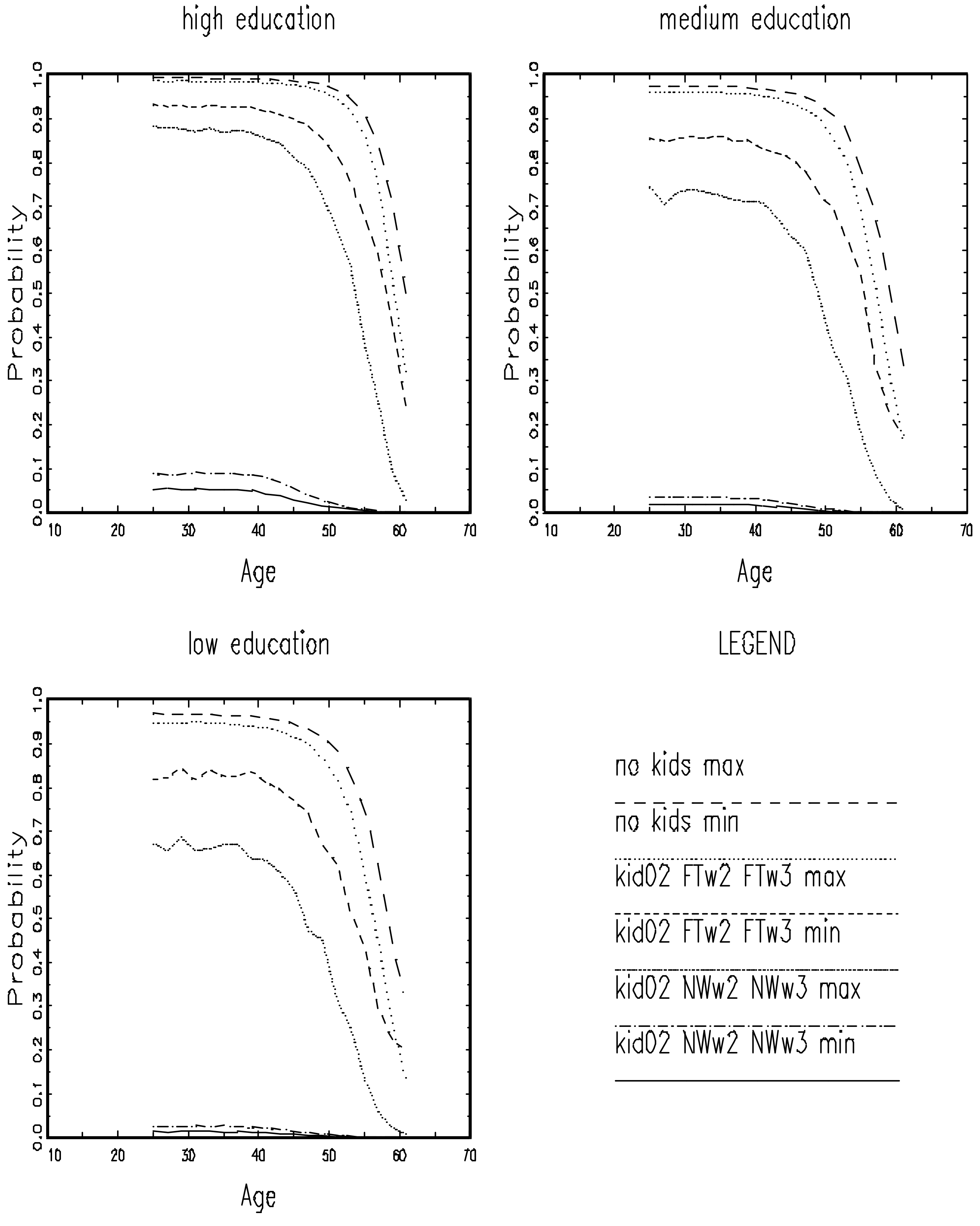

Figure 15. Direct and indirect effects in wave 5, age of the child held constant. Probabilities are calculated conditional on full-time employment in wave 1.

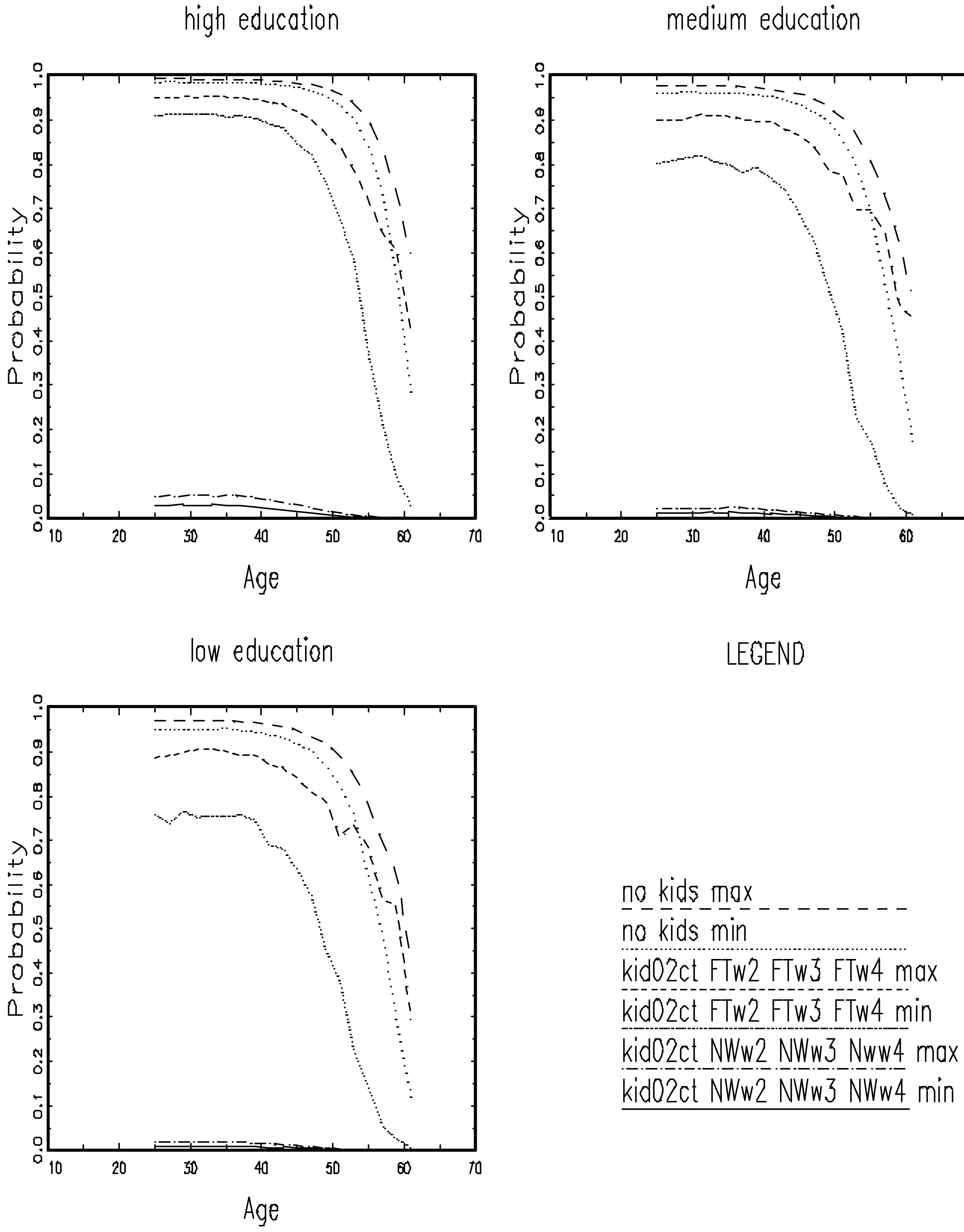

Figure 16. Direct and indirect effects in wave 5, child in age catagory 3-5. Probabilities are calculated conditional on full-time employment in wave 1.

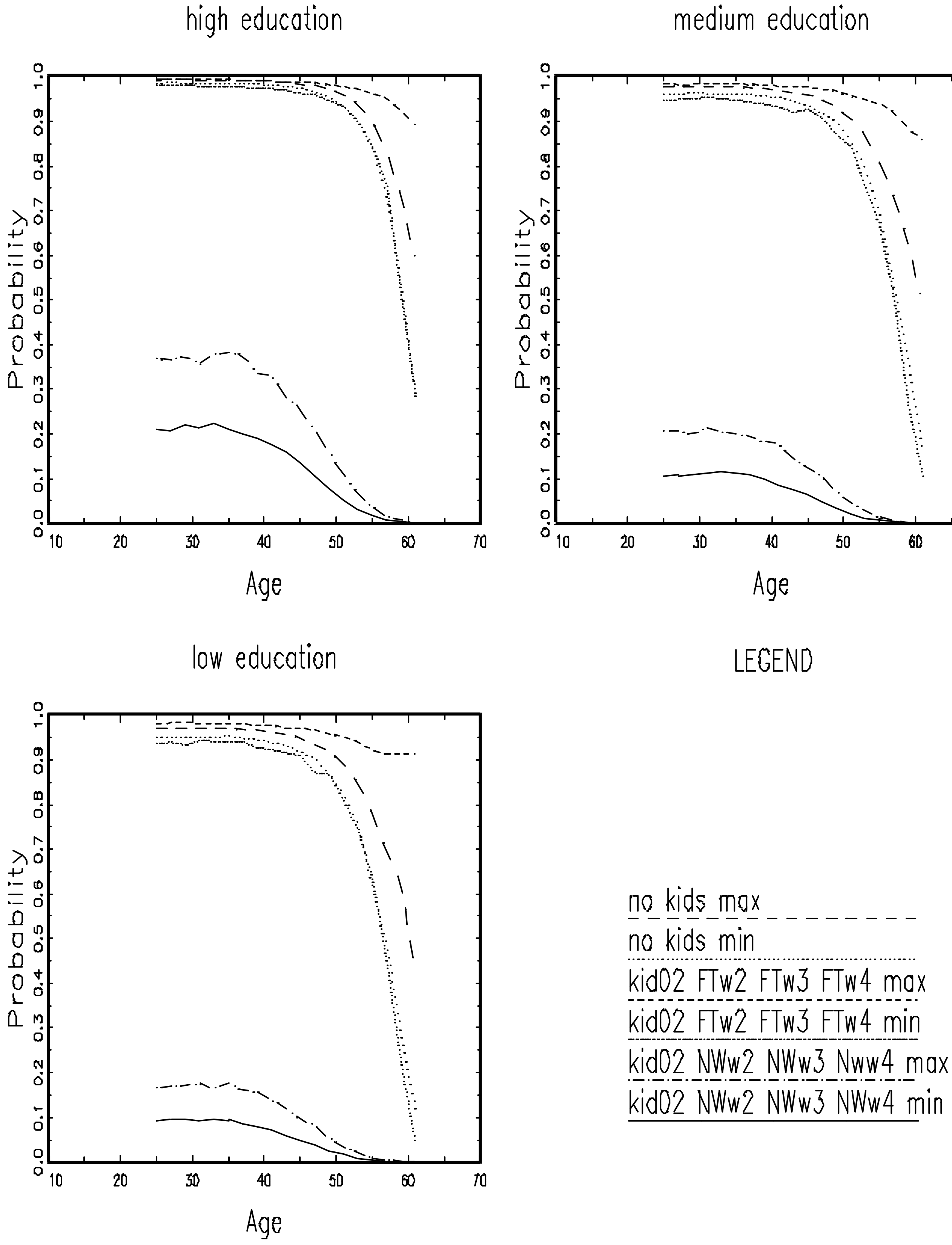

Figure 17. Comparison of the indirect effects with age held constant. Probabilities are calculated conditional on full-time employment in wave 1.