

# Determinants of Poverty Status in Taiwan: A Multilevel Approach

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**Abstract** The aim of this study was to analyze the determinants of poverty in Taiwan, including family-level and regional-level factors. In contrast to previous studies, which have overlooked the interrelationships between individuals, families, and social structures because of methodological limitations, we applied hierarchical generalized linear models to a hierarchical structure. We used multiple data sources collected by the Directorate General of Budget, Accounting, and Statistics in the Taiwanese Executive Yuan, including the 2006 Survey of Family Income and Expenditure, the 2006 National Statistics, and the 2006 Manpower Utilization Survey. We examined 13,640 households from 23 cities and counties (regions). Our results indicated that poverty risks vary by region. Among the family-level factors studied, education, socioeconomic status, age, family type, dependency ratio, marital status, and number of earners are connected to poverty status. Significant relationships were also observed between poverty and structural characteristics, such as economic inequality, economic growth, structural transition, and labor market characteristics. We also attempted to detect cross-level interactions between family-level and regional-level factors. Surprisingly, none of the cross-level interactions were statistically significant. This article presents the unexpected results and research limitations.

**Keywords** Determinants of poverty · Hierarchical generalized linear model (HGLM) · Multilevel logistic regression · Poverty

# 1 Introduction

Poverty has increased in Taiwan over the past 2 decades. According to government statistics, the official poverty rate has steadily increased. The household poverty rate increased from 0.82 % in 1992 to 1.79 % in 2013 (Ministry of Health and Welfare 2014).

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Department of Social Welfare, National Chung Cheng University, 168 University Road, Minhsiung Township, Chiayi County 62102, Taiwan, ROC e-mail: corachen0930@gmail.com Growing income inequality reflects a widening income gap between the rich and poor. Empirical studies have determined that income inequality negatively affects poverty (Iceland 2003; Apergis et al. 2011; Fosu 2010; Wang et al. 2008). In Taiwan, the Gini coefficient has increased from 0.283 to 0.338 over the last 3 decades (National Statistics 2012), and this wide disparity is more detrimental to the poor.

Poverty might vary by country, region, and group, but it affects individuals and families either directly or indirectly. Low-income people might experience lower levels of wellbeing. For example, Lever et al. (2005) reported that high consumption was positively associated with the subjective well-being of people living in Mexico City. Furthermore, children who live in poverty are likely to suffer from low levels of well-being related to their health, cognitive development, academic achievement, aspirations, self-perceptions, peer and family relationships, risk behavior, and employment prospects (UNICEF 2007). Studies have analyzed the link between poverty and the well-being of children (Ozawa et al. 2004; Prince et al. 2006; Bradshaw et al. 2007; OECD 2009; Brooks-Gunn and Duncan 1997; Diener and Tay 2013). Ozawa et al. (2004) used multiple indicators, including mean income, child poverty rate, and income inequality, to examine the well-being of children in the United States. They concluded that economic deprivation adversely affects child well-being across the United States. These studies have demonstrated that the consequences of poverty are harmful to disadvantaged groups.

In Taiwan, the government and researchers have examined strategies for poverty reduction since the 1970s. The government initiated a "plan to help the needy" to eliminate causes of poverty through antipoverty policies that first became a political target in 1972 (Chang 1996). However, the fight against poverty has failed and the plight of the poor has not improved. An increasing number of people in Taiwan face economic hardship.

Several studies have indicated that poverty is attributable to individual and structural factors in Taiwan (Chang 1992a; Leu 1995, 1996; Huang 2000; Hsueh 2002, 2004; Leu 2010b; Tsai 1994; Tsai and Huang 2007). Nevertheless, these studies have overlooked the interrelationships between individuals, families, and social structures because of methodological limitations. Therefore, this study adopted a multilevel approach. International studies have used multilevel analysis to examine factors of poverty by considering micro- and macrolevel variables in Western welfare states (Kim et al. 2010), and to analyze how family policy institutions affect child poverty in 21 old and new welfare states (Bäckman and Ferrarini 2010).

Multilevel modeling techniques enable the incorporation of different levels into a single comprehensive model to avoid model misspecification, and facilitate the exploration of causal heterogeneity by inspecting cross-level interactions (Steenbergen and Jones 2002). This study examined the determinants of poverty in Taiwan by using multilevel models. We attempted to answer the following questions: (a) Do poverty risks vary across regions (including cities and counties); (b) What family-level factors contribute to poverty; (c) What regional-level factors are related to poverty after controlling for family-level factors; and (d) What regional-level factors moderate the relationship between family-level factors and poverty risks? We included regional-level factors to detect cross-level interactions.

#### 2 Literature Review

The literature has broadly discussed the causes of poverty and studies are divided into individual and structural explanations. However, these distinctions fail to reflect the relationship between individual and family characteristics. Individual explanations of poverty are closely connected with the individual characteristics and family context. We treated households as resource sharing units. Therefore, family dimensions should be examined to explore the causes of poverty from family-level and structural perspectives.

#### 2.1 The Family-Level Perspective

Poverty is linked to individual characteristics and family contexts. Lewis (1969) proposed the culture of poverty as an individual explanation of poverty. The increasing number of people living in poverty might result from the vicious cycle of poverty (Harrington 1981). People living in a culture of poverty exhibit a unique lifestyle based on their social circumstances. They develop pathological behaviors and attitudes and feel alienated from mainstream society. The culture of poverty is self-perpetuating; negative characteristics, such as helplessness, fatalism, and inferiority are passed from one generation to the next (Lewis 1969). Thus, the poor are caught in a vicious cycle and trapped in poverty.

Another essential aspect of poverty is a lack of human capital. Human capital theory maintains that household resources are related to the amount of human capital investment. Limited resources cannot facilitate human capital accumulation among children living in poverty. The poor cannot earn higher wages in the labor market because they lack education and skills. From a theoretical perspective, the concept of human capital involves family investments (Becker 1993). Human capital theory implies that family exerts a crucial influence on an individual's socioeconomic status, which can determine whether a person falls into poverty.

Family context is associated with poverty. Over the last 3 decades, many studies have shown how changes in family structure affect poverty (Albrecht et al. 2000; Eggebeen and Lichter 1991; Ellwood 1988; Ellwood and Crane 1990; Garfinkel and McLanahan 1988; Hoynes et al. 2006; Iceland 2003; McLanahan et al. 1988; Smith 1988). For instance, single-parent families are more likely to be poor than two-parent families (Ellwood 1988; Cancian and Reed 2000), and female-headed families are more likely to be poor than male-headed families (Hoynes et al. 2006).

Research indicates that poverty in Taiwan might be attributed to the family structure (Chang 1992a). The gender and age of household heads, family type, marital status, and household dependency ratio are related to poverty. Female-headed, single-parent, and female-headed single parent families are more likely to experience poverty (Leu 1995, 1996; Huang 2000; Hsueh 2000, 2004). The poverty rate of single-person households aged 65 years and above is higher than in younger households. In particular, women and the widowed are more likely to live in poverty among single-person households aged 65 years and above (Hsueh 2002). Marital status also contributes to poverty. Widowed families have a higher probability of being poor than married families have, and married families are more likely to be poor than unmarried families (Leu 1995). Leu (1995) also noted that households with higher dependency ratios might increase the risk of poverty.

These causes of poverty depend on micro-level explanations. It is difficult to examine the causes of poverty from a single dimension because individuals and households are connected to social structures. The interaction between micro- and macrolevel factors reflects this connection. The following section presents a discussion of the structural explanation of poverty.

#### 2.2 Structural Perspectives

Studies have attempted to examine poverty from structural perspectives, including dual labor theory, trickle-down theory, and industrial transition theory. According to dual labor theory, the labor market is separated into a primary and a secondary labor market. The following

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factors distinguish the two labor markets: employment stability, working conditions, skill requirements, wages, opportunities for promotion, and work rules. In contrast to the secondary sector, the primary sector is characterized by relatively stable jobs, high wages, favorable working conditions, skilled jobs, abundant promotion opportunities, and fair work rules (Doeringer and Piore 1971). Poor workers are typically confined to the secondary sector because of unstable work histories that are typically not accepted by employers in the primary sector (Rank 2001). In other words, the labor market structure prevents the disadvantaged from entering the primary labor market and keeps them in poverty.

Another approach to explaining poverty is the trickle-down effect, which assumes that economic growth can reduce poverty. This is a diffusion process from the rich to the poor. When the rich become richer, their wealth trickles down to the poor. Anderson (1964) indicated that economic growth tends to eliminate poverty, but the effect of economic growth on poverty reduction is different at various stages of economic growth. With an increase in median income, the effect of economic growth on poverty first increases and then decreases. Dollar and Kraay (2002) supported the advantages of economic development, and they argued that people can benefit from economic growth, whether they are rich or poor. Likewise, Tsai and Huang (2007) concluded that economic growth influenced poverty reduction from 1964 to 2003 in Taiwan.

The effect of economic growth on poverty reduction is different when various measurements are applied to different countries, regions, sectors, and periods. For example, Freeman (2003) stated that, compared with national-level data, regional-level data showed a negative correlation between the poverty rate and unemployment rate after controlling for demographic and structural variables during the 1980s and 1990s. Montalvo and Ravallion (2010) also examined economic growth and poverty patterns across sectors and regions in China. They observed that the effect of economic growth was highly uneven across sectors, although growth did contribute to poverty reduction. In contrast to the manufacturing and service sectors, the growth rate of the agriculture sector helped alleviate poverty. Additionally, the trickle-down effect depends on how the term "economic growth" is defined. Adams (2004) concluded that the growth elasticity of poverty varied based on whether economic growth was measured using changes in mean income (consumption) or changes in GDP per capita. The poverty-reduction effect in 60 developing countries was larger when changes in mean income (consumption) were used to measure economic growth.

Studies have determined that the plight of the poor has not improved when the economy flourishes (Ashley 2008; Foster and Székely 2008; Smolensky et al. 1994; Leu 2010b). For example, in the U.S. economy in the 1980s, economic expansion did not trickled down to the vulnerable because of structural changes, such as industrial transition, mass customization, and the polarization of employment and wages (Kelso 1994). The U.S. economy underwent industrial transition during the shift from manufacturing to service industries when entering a postindustrial society in the 1970s and 1980s (Wilson 1987). Structural transition is closely related to poverty rates (Albrecht et al. 2000; Tickamyer and Duncan 1990; Tomaskovic-Devey 1988; Tsai 1994, 1996). Tsai (1996) examined the causes of poverty in Taiwan from 1971 to 1991. Regional differences existed between industrial structures and poverty rates. Service sector expansion was related to high poverty rates in metropolitan areas. Conversely, the manufacturing sector that did not require high education and skill levels decreased poverty rates in nonmetropolitan areas.

Structural transformation also caused skills and spatial mismatch problems in U.S. inner cities. A skills mismatch means that low education and poor skills among the disadvantaged do not match the employment requirements in the labor market. A spatial mismatch reflects a mismatch between employment opportunities and residential locations. Bluecollar jobs with lower education and skill requirements moved to the suburbs, leading to decreased employment opportunities in the inner cities (Kasarda 1988, 1993; Wilson 1987). The poor have dropped out of the labor market because of urban mismatches, which limit their upward mobility and make it difficult to escape poverty.

#### 3 Methodology

#### 3.1 Data Description

The multiple data sources used in this study were mainly collected by the Directorate General of Budget, Accounting, and Statistics (DGBAS) in the Taiwanese Executive Yuan, including the 2006 Survey of Family Income and Expenditure (SFIE), the 2006 National Statistics (NS), and the 2006 Manpower Utilization Survey (MUS). The study included 13,640 households from 23 cities and counties (regions) in Taiwan. The sample size within these regions ranged from 192 in Penghu County to 1,979 in Taipei City. The SFIE employed a stratified two-stage sampling method that results in clustered data; thus it allowed us to analyze two levels of hierarchical data: family-level (Level 1) and regional-level (Level 2) data. We could identify the regions in which households resided because the SFIE featured a hierarchical data structure and the SFIE data were combined with aggregate data provided by the NS and MUS. The family-level data and some of the regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the SFIE and the remaining regional-level data were obtained from the S

#### 3.2 Dependent Variable

The dependent variable was poverty status, which was treated as a binary outcome (Y = 0or 1). Setting the poverty thresholds at 50 or 60 % of the median equivalised household income is a conventional approach to defining poverty (Mitchell 1991; Smeeding et al. 2001). In this study, households were defined as poor if they earned less than 50 % of the median equivalised household income; this threshold is commonly used in Taiwan. Hence, households with income below the poverty level were coded 1, and households with income above the poverty level were coded 0. We considered the effects of tax and government transfers on poverty status; therefore household income was measured as market income, which reflects income before tax and government transfers. An equivalence scale was used to adjust poverty thresholds to reflect differences in family needs (Ruggles 1990). The Organization for Economic Cooperation and Development (OECD) equivalence scale has been commonly used in poverty research (e.g., Buhmann et al. 1988; Atkinson et al. 1995; Citro and Michael 1995; Quintanaa and Malob 2012). We used a four-person family as a reference family and a modified OECD equivalence scale to adjust the poverty thresholds in the study. The scale allocated a weight of 1 to the household head, 0.5 to each additional adult member aged 15 years or older, and 0.3 to each child under the age of 15 years (Hagenaars et al. 1994). The following equation represents this allocation:

$$S(A,K) = (1+0.5 \times (A-1) + 0.3 \times K)^{1}$$
(1)

where S(A, K) is the equivalence scale, A is the number of adult people, and K is the number of children.

# 3.3 Independent Variables

As shown in Table 1, the independent variables were divided into family-level and regional-level factors. Individual characteristics are embedded in a family context and individuals form part of households. We assumed that household members shared resources and regarded a household as the unit of analysis. Therefore, family-level variables comprised individual and family characteristics. Individual characteristics included the education level, socioeconomic status, age, and gender of the household head; and family characteristics were composed of the family type, household dependency ratio, marital status, and number of earners. Gender was coded as a dummy variable. Other than the dependency ratio and number of earners, the variables were measured as discrete

Variables	Description	Sources
Dependent variable		
Poverty status	0: Living above the poverty line 1: Living below the poverty line	SFIE
Independent variable		
Family-level		
Educational attainment	1: Primary or less than primary school, 2: Junior high school, 3: Senior high school, 4: College degree, 5: Above college	SFIE
Socioeconomic status	1: Low, 2: Medium, 3: High	SFIE
Age	Under age 30, age 30–64 (reference group), age 65 and over	SFIE
Gender	0: Male, 1: Female	SFIE
Family type	Couple family, nuclear family, single parent family, grandparent family, extended family, and other types (including one-person and other families; reference group)	SFIE
Dependency ratio	Total number of non-working members as a percentage of the total number of members in the household	SFIE
Marital status	Married (including cohabited), divorced (including separated), widowed, and unmarried (reference group)	SFIE
Number of earners	Number of earners in the household	SFIE
City- and county-level		
Income inequality	Theil index	SFIE
Employment-to-population ratio	The ratio of the employed individuals aged 15 years and over to people aged 15 years and over	NS
Service to manufacturing ratio	The ratio of employment in the service industry to employment in the manufacturing industry	NS
Spatial mismatch	Total number of employed persons who did not work in residential locations as a percentage of total number of employees	SFIE
Job quality	The ratio of people whose weekly working hours greater than 40 and income less than minimum wage to the labor force	MUS

 Table 1
 Descriptions of variables in the analysis

variables. To a certain extent, family-level variables reflected concepts relevant to human capital and family structures that are related to poverty risk.

All regional-level variables were continuous variables, including income inequality, employment-to-population ratio, service to manufacturing ratio, spatial mismatch, and job quality. Data were extracted from the SFIE, NS, and MUS, as shown in Table 1. Based on the theoretical background, income inequality and the employment-to-population ratio are related to economic growth; and service to manufacturing ratio, spatial mismatch, and job quality reflect the characteristics of industrial structures.

We used the Theil index proposed by Theil (1967) to measure income inequality. The Theil index has been widely applied in the analysis of economic inequality across countries, regions, or groups (e.g., Theil 1989; Akita 2003; Gray et al. 2004). Higher values reflect greater inequality, which leads to rising poverty levels (Apergis et al. 2011; Iceland 2003; Wang et al. 2008). The employment-to-population ratio is related to economic growth, and was calculated as the ratio of employed individuals aged 15 years and over to the entire population (only people 15 years and older were included).

Research has shown that a structural transition is critical to poverty rates (Wilson 1987; Kasarda 1993). A structural transition refers to a shift from the manufacturing industry to the service industry. We measured the service to manufacturing ratio by using the ratio of employment in the service industry to employment in the manufacturing industry. A spatial mismatch refers to a mismatch between employment and residential locations or jobs and workers (Ellwood 1986). Spacial mismatch is related to structural transition. The mismatch problem increases unemployment among low-skilled and low-educated workers because of industrial transition. We used the mismatch between employment and residential locations as an indirect measure of spatial mismatch; namely, the total number of employed persons who did not work in residential locations as a percentage of the total number of employees. Working conditions reflect the quality of a job. Low-skilled and low-educated workers typically serve the secondary labor market, and they are more likely to live in poverty.

### 3.4 Hierarchical Generalized Linear Models

If binary variables are examined, it is appropriate to apply multilevel logistic regression analysis, also called hierarchical generalized linear models (HGLMs), to analyze nonlinear structural models (Raudenbush and Bryk 2002). Multilevel modeling was applied to clustered structures, indicating that households (Level 1) were nested within regions (Level 2), and can exert cross-level interaction effects. Using conventional statistical models to analyze multilevel data is problematic. Conventional models assume that low-level observations are independent. Multilevel data violate this assumption of observation independence, leading to biased standard errors and inflated Type I error rates<sup>1</sup> (Hox 2010; Hox and Maas 2005; Steenbergen and Jones 2002). The ecological fallacy and atomistic

<sup>&</sup>lt;sup>1</sup> When a traditional linear model is applied to analyze a hierarchical data structure, it causes the dependence of the observations at the first level, which can be measured according to an intraclass correlation. The presence of an intraclass correlation causes the standard errors of the regression coefficients to be underestimated and the type I error rates to increase (the alpha level,  $\alpha$ ). The null hypothesis is easily rejected (Heck and Thomas 2009; Kreft and De Leeuw 1998). Moreover, the statistical power indicating the probability that a null hypothesis is correctly rejected increases when  $\alpha$  is set at a higher level (Hox, 2010). If we were to use OLS regression to analyze the multilevel data structure, the OLS estimators would be incorrect because the small standard errors increase the power (Kreft and De Leeuw 1998). See Barcikowski (1981) and Kreft and De Leeuw (1998) for more detailed discussions.

fallacy can also lead to incorrect inferences (Hox 2010). Therefore, multilevel modeling techniques were suitable for this study.

Eight models were used to answer the research questions in this study. A null model (Model 1) was estimated, which served as a benchmark for comparison with other models. We then determined if it was necessary to develop multilevel models (Hox 2010; Luke 2004). A random coefficient model (Model 2) containing family-level variables and permitting varying intercepts and slopes was then fitted to examine whether poverty risks varied by region. This model was used to explore the family-level factors that contributed to poverty. An intercepts-as-outcomes model (Model 3) was applied to assess the relationship between regional-level factors and poverty risks after controlling for family-level factors. We included cross-level interactions to model the influence of structural characteristics on poverty. The intercepts and slopes as outcomes models were then estimated (Models 4–8).

The intercepts and slopes as outcomes model constitutes a full multilevel model that can be defined as

$$\log\left(\frac{P_{ij}}{1 - P_{ij}}\right) = \log \operatorname{it}(\eta_{ij}) = \gamma_{00} + \sum_{q=1}^{Q} \gamma_{0q} Z_{qj} + \sum_{g=1}^{G} \gamma_{g0} X_{gij} + \sum_{g=1}^{G} \sum_{q=1}^{Q} \gamma_{gq} X_{gij} Z_{qj} + \sum_{g=1}^{G} u_{gj} X_{gij} + u_{0j}$$
(2)

$$\begin{pmatrix} u_{0j} \\ u_{gj} \end{pmatrix} \sim N\left( \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \tau_{00} \ \tau_{0g} \\ \tau_{g0} \ \tau_{gg} \end{pmatrix} \right)$$
(3)

where  $P_{ij}$  is the probability that the *i*th household in the region *j* is poor;  $logit(\eta_{ij})$  denotes the logistic link function for binary data;  $\gamma_{00}$  is the intercept;  $X_{gij}$  represents *g* explanatory variables at the family level;  $Z_{qj}$  represents *q* explanatory variables at the regional level;  $\sum_{q=1}^{Q} \gamma_{0q}$  and  $\sum_{g=1}^{G} \gamma_{g0}$  are the regression coefficients related to the regional level and family level, respectively; and  $\sum_{g=1}^{G} \sum_{q=1}^{Q} \gamma_{gq}$  represents the cross-level interaction effects between family-level and regional-level variables. Moreover,  $\sum_{g=1}^{G} u_{gj}X_{gij} + u_{0j}$  represents random effects. The terms  $u_{0j}$  and  $u_{gj}$  are regional-level residuals. Assume that both *u* terms follow a normal distribution with means of zero and variances of  $\tau_{00}$  and  $\tau_{gg}$ .

Equation 2 is a combined model consisting of level-1 (family-level) and level-2 (regionlevel) models expressed as

Level 1 : 
$$\ln\left(\frac{P_{ij}}{1-P_{ij}}\right) = \operatorname{logit}(\eta_{ij}) = \beta_{0j} + \beta_{gj} \sum_{g=1}^{G} X_{gij}$$
 (4)

Level 2 : 
$$\beta_{0j} = \gamma_{00} + \sum_{q=1}^{Q} \gamma_{0q} Z_{qj} + u_{0j}$$
  
 $\beta_{1j} = \gamma_{10} + \sum_{q=1}^{Q} \gamma_{1q} Z_{qj} + u_{1j}$ 
(5)

$$\beta_{gj} = \gamma_{g0} + \sum_{q=1}^{Q} \gamma_{gq} \mathbf{Z}_{qj} + u_{gj}$$

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where  $\beta_{0j}$  and  $\beta_{gj}$  are intercept and slope coefficients, respectively. It is assumed to be a random variable with mean 0 and variance  $\sigma^2$  in the level-1 model. The variance of the standard logistic distribution is equal to  $\pi^2/3$ .

In multilevel modeling, three types of parameter can be estimated: fixed effects, firstlevel random effects, and variance–covariance components. Three methods are used for parameter estimation, namely full maximum likelihood (ML), restricted maximum likelihood (REML), and Bayesian methods. However, these methods are not appropriate for a discrete outcome. The parameters in HGLMs which require more complex methods and estimation procedures are estimated using penalized quasi-likelihood estimation (PQL) (Raudenbush and Bryk 2002). The estimation procedure was implemented in an HLM program designed for analyzing the hierarchical data structures in this study.

#### 4 Empirical Results

The poverty rate in Taiwan was estimated at approximately 13.7 %. The poverty rate varies substantially by region, ranging from 3.18 to 36.5 % (see Fig. 1). Table 2 shows a summary of the descriptive statistics of the independent variables.

The null model was used as a preliminary model to determine whether between-group variability existed. Table 3 presents the parameter estimates for Models 1–3. Model 1 is a null model that excluded family-level and region-level predictors. The statistically significant between-group variance of 0.489 indicated that average poverty risks varied by region ( $\chi^2 = 757.697$ , p < .001). The expected log odds of poverty was -1.679, with a variance of 0.489. Thus, we expected 95 % of poverty risk to occur between 0.047 and 0.735,<sup>2</sup> reflecting considerable variability across regions. We also calculated the intraclass correlation coefficient (ICC) to measure the proportion of variance in the population explained by the groups (Hox 2010; Raudenbush and Bryk 2002), which is expressed as  $\rho = \tau_{00}/(\tau_{00} + \sigma^2) = 0.489/(0.489 + 3.29) = 0.129$ .<sup>3</sup> The estimated ICC indicated that 12.9 % of the poverty risk variance was explained at a regional level, implying that a multilevel model was necessary.

In Table 3, Model 2 (the random coefficient model) included family-level variables and allowed intercepts and slopes to vary across Level 2. The estimated variance of 1.761 for the intercept was significantly different from zero ( $\chi^2 = 48.793$ , p < .01), indicating that, on average, significant differences existed between regional poverty risks after controlling for family-level variables. Moreover, most family-level variables were significantly associated with poverty, except for household heads younger than 30 years old and childless families. Several factors decreased the log odds of poverty: educational attainment; socioeconomic status; married, divorced, and widowed families; and the number of earners. Regarding the variance components of the slopes, only the dependency ratio was significantly different from zero (p < .001), implying that the effect of the dependency ratio on poverty varied by region. For simplicity, the variance of the slopes for the family-level variables is not listed in Table 3.

An intercepts-as-outcomes model was estimated. We introduced regional-level factors to examine the relationship between poverty risks and regional-level factors when

<sup>&</sup>lt;sup>2</sup> The range of log odds for poverty was  $-1.679 \pm 1.96 \times \sqrt{0.489} = (-3.050, -0.308)$  and the corresponding odds ratios were (0.047, 0.735).

<sup>&</sup>lt;sup>3</sup> The variance of the Level 2 residuals ( $\tau_{00}$ ) was 0.489 and the variance of the standard logistic distribution ( $\sigma^2$ ) was equal to  $\pi^2/3 = 3.29$ .



Fig. 1 The poverty rate by region

controlling for family-level factors. The slopes of the family-level factors were treated as random, and were allowed to vary across regions. Model 3 indicated that regional-level factors were significant and explained 57  $\%^4$  of the regional variance, or twice as much as Model 2. This proved that these regional-level factors should be included. The results of Model 3 regarding the effect of family-level factors on poverty and the variation of poverty risks and slopes among regions were similar to the results of Model 2. Nevertheless, divorced marital status was not statistically significant after controlling for regional-level variables.

Model 3 provided valuable information concerning regional-level factors. All the structural factors significantly influenced the log odds of poverty. More specifically, a strongly positive relationship between income inequality and poverty was identified. The employment-to-population ratio related to economic development positively affected poverty reduction. The log odds of poverty declined as the ratio of employment in the service industry to employment in the manufacturing industry increased. Another factor related to industrial characteristics is spatial mismatch, which demonstrated that as the percentage of employed people who did not work in residential areas increased, people were more likely to fall into poverty. Job quality is a labor market characteristic. As expected, poor job quality is a substantial contributor to poverty.

Table 4 shows the results of the intercepts and slopes as outcomes models by introducing cross-level interactions. We attempted to determine which regional-level factors moderated the relationship between family-level factors and poverty risks. Thus, we specified these models to include family-level and region-level factor interactions. According to Models 2 and 3, the intercept was random. At the family level, only the dependency ratio slope was statistically significant, indicating that the effect of the dependency ratio on poverty varied across regions. Therefore, the intercept and dependency ratio were treated as random and interacted with each regional-level variable, whereas the remaining explanatory variables did not.

<sup>&</sup>lt;sup>4</sup> This is called proportion variance explained, and is calculated using  $\tau_{00}$  (Model 2) –  $\tau_{00}$  (Model 3)/  $\tau_{00}$  (Model 2). See Raudenbush and Bryk (2002) and Hox (2010) for more detailed discussions.

**Table 2** Descriptive statistics ofindependent variables

Variables	No. (% of total)
Family-level (n = $13,640$ )	
Educational attainment	
Primary or less than primary school	3,212 (23.55)
Junior high school	2,243 (16.44)
Senior high school	4,054 (29.72)
College degree	3,629 (26.61)
Above college	502 (3.68)
Socioeconomic status	
Low	6,299 (46.18)
Medium	5,626 (41.25)
High	1,715 (12.57)
Age	
Under age 30	831 (6.09)
Age 30–64	10,742 (78.75)
Age 65 and over	2,067 (15.15)
Gender	
Male	10,458 (76.67)
Female	3,182 (23.33)
Family types	
Couple family	2,127 (15.59)
Single parent family	1,192 (8.74)
Nuclear family	5,997 (43.97)
Grandparent family	164 (1.20)
Extended family	1,997 (14.64)
Other types	2,163 (15.86)
Dependency ratio [Mean (SD)]	1.89 (1.27)
Marital status	
Married/cohabited	9,730 (71.33)
Divorced/separated	986 (7.23)
Widowed	1,019 (7.47)
Unmarried	1,905 (13.97)
Number of earners [Mean (SD)]	1.64 (0.81)
City- and county-level $(n = 23)$	
Income inequality [Mean (SD)]	0.19 (0.05)
Employment-to-population ratio [Mean (SD)]	53.88 (1.79)
Service to manufacturing [Mean (SD)]	2.03 (1.04)
Spatial mismatch [Mean (SD)]	54.35 (9.15)
Job quality [Mean (SD)]	4.17 (2.80)

Table 4 reveals a similar finding of significant variation across regions. Each model indicated a substantial reduction in the proportional variance explained in Level 2—ranging from 65 to 72 %—when the cross-level interactions were included. This implied that these cross-level interactions must be taken into account. Surprisingly, none of the cross-level interactions were statistically significant at the 5 % level. The effect of the

	Model 1		Model 2		Model 3	
	Coefficients	SE	Coefficients	SE	Coefficients	SE
Family-level variables						
Intercept	-1.679***	(0.148)	-0.640	(0.359)	5.154***	(1.274)
Educational attainment			-0.563***	(0.044)	-0.554***	(0.046)
Socioeconomic status			-0.664***	(0.069)	-0.668***	(0.071)
Age						
Under age 30			0.137	(0.099)	0.134	(0.103)
Age 65 and over			0.686***	(0.088)	0.735***	(0.084)
Female			0.280***	(0.067)	0.305***	(0.067)
Family type						
Couple family			0.212	(0.155)	0.204	(0.158)
Single parent family			1.164***	(0.125)	1.154***	(0.129)
Nuclear family			0.872***	(0.132)	0.865***	(0.135)
Grandparent family			0.887***	(0.215)	0.879***	(0.211)
Extended family			2.001***	(0.153)	1.989***	(0.155)
Dependency ratio			2.525***	(0.234)	2.394***	(0.227)
Marital status						
Married			$-0.383^{***}$	(0.099)	-0.379***	(0.099)
Divorced			-0.247*	(0.118)	-0.240	(0.119)
Widowed			$-0.931^{***}$	(0.140)	-0.948***	(0.140)
Number of earners			$-0.901^{***}$	(0.072)	-0.928***	(0.070)
City- and county-level						
Income inequality					6.516***	(0.460)
Employment-to-population ratio					-0.132***	(0.024)
Service to manufacturing					-0.597 ***	(0.057)
Spatial mismatch					0.013*	(0.006)
Job quality					0.104***	(0.018)
Variance components	Variances	$x^2$	Variances	$x^2$	Variances	$x^2$
Level 2 variance	0.489***	757.697	1.761**	48.793	0.756*	33.260

Table 3 HGLM analysis for determinants of poverty

For simplicity, the estimated of the slopes for the family-level variables is not listed here in Model 3 \* p < .05, \*\* p < .01, \*\*\* p < .001

dependency ratio on poverty was not moderated by regional-level variables. In the following section, we discuss possible reasons for the unexpected results.

Regarding each model, the results of all the family-level factors were consistent with Model 3, except for the household dependency ratio. Household heads younger than 30 years old, childless families, and divorced marital status were not significantly related to poverty. The results of Models 5 and 7 were slightly different from the results of Model 3. The cross-level interactions relative to the regional-level factors in Models 5 and 7 indicated that the household dependency ratio did not significantly affect the log odds of poverty. At the regional-level, all variables reduced the probability of falling into poverty, except for spatial mismatch. This implied that the effect of spatial mismatch on poverty disappeared when each model introduced cross-level interactions.

Table 4 Cross-level interactions fo	or determinants of pove-	rty			
	Model 4 +Income inequality	Model 5 +Employment-to-population ratio	Model 6 +Service to manufacturing	Model 7 +Spatial mismatch	Model 8 +Job quality
Family-level variables (X)					
Intercept	5.737** (1.532)	9.112* (4.107)	$5.918^{**}(1.540)$	6.799*** (1.654)	5.687** (1.686)
Educational attainment	$-0.535^{***}$ (0.043)	$-0.535^{***}$ (0.043)	$-0.535^{***}$ (0.043)	$-0.536^{***}$ (0.044)	$-0.536^{***}$ (0.043)
Socioeconomic status	$-0.675^{***}$ (0.071)	$-0.677^{***}$ (0.070)	$-0.680^{***}$ (0.069)	$-0.674^{***}$ (0.068)	$-0.668^{***}$ (0.068)
Age					
Under age 30	0.124(0.103)	0.123 (0.103)	0.123 (0.103)	0.122(0.103)	0.123 (0.103)
Age 65 and over	$0.722^{***}$ (0.091)	0.724*** (0.090)	$0.727^{***}$ (0.088)	$0.720^{***} (0.089)$	$0.713^{***}$ (0.089)
Female	$0.276^{***}$ (0.070)	0.277 * * * (0.070)	0.277*** (0.070)	$0.277^{***}$ (0.070)	$0.276^{***}$ (0.070)
Family type					
Couple family	0.193 (0.155)	0.193 (0.155)	0.194 (0.156)	0.192 (0.155)	0.190 (0.155)
Single parent family	$1.103^{***} (0.137)$	$1.100^{***} (0.135)$	$1.100^{***} (0.135)$	$1.102^{***} (0.135)$	$1.106^{***} (0.136)$
Nuclear family	0.830*** (0.127)	0.829*** (0.127)	$0.830^{***}$ (0.128)	$0.830^{***} (0.127)$	0.831*** (0.127)
Grandparent family	0.857*** (0.223)	0.857*** (0.223)	$0.858^{***}$ (0.222)	$0.855^{***} (0.223)$	$0.856^{***}$ (0.223)
Extended family	$1.926^{***} (0.160)$	$1.925^{***}$ (0.160)	$1.926^{***}$ (0.160)	$1.926^{***} (0.161)$	$1.925^{***}$ (0.160)
Dependency ratio	$2.845^{***}$ (0.613)	-1.486 (4.914)	2.564*** (0.552)	1.301 (1.156)	2.837*** (0.365)
Marital status					
Married	$-0.380^{***}$ (0.100)	$-0.381^{***}$ (0.099)	$-0.379^{***}$ (0.099)	$-0.383^{***}$ (0.099)	$-0.383^{***}$ (0.099)
Divorced	-0.216(0.118)	-0.216 (0.118)	-0.214 (0.119)	-0.220(0.118)	-0.220(0.118)
Widowed	$-0.930^{***}$ (0.135)	$-0.930^{***}$ (0.136)	$-0.928^{***}$ (0.136)	$-0.935^{***}$ (0.136)	$-0.931^{***}$ (0.136)
Number of earners	$-0.932^{***}$ (0.065)	$-0.933^{***}$ (0.065)	$-0.934^{***}$ (0.065)	$-0.936^{***}$ (0.065)	$-0.931^{***}$ (0.065)
City- and county-level (Z)					
Income inequality	8.655*** (2.094)	6.469*** (0.506)	$6.438^{***}$ (0.499)	$6.488^{***} (0.511)$	$6.526^{***}$ (0.528)
Employment-to-population ratio	$-0.149^{***}$ (0.029)	-0.203*(0.075)	$-0.148^{***}$ (0.029)	$-0.146^{***}$ (0.029)	$-0.147^{***}$ (0.028)
Service to manufacturing	$-0.560^{***}$ (0.074)	$-0.557^{***}$ (0.075)	-0.420*(0.195)	$-0.558^{***}$ (0.075)	$-0.561^{***}$ (0.074)
Spatial mismatch	0.011 (0.007)	0.011 (0.007)	0.011 (0.007)	-0.004 (0.017)	0.011 (0.007)

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Table 4 continued					
	Model 4 +Income inequality	Model 5 +Employment-to-population ratio	Model 6 +Service to manufacturing	Model 7 +Spatial mismatch	Model 8 +Job quality
Job quality	$0.115^{***} (0.021)$	$0.114^{***}$ (0.021)	0.114 * (0.021)	$0.115^{***} (0.021)$	0.193*** (0.050)
Variance components					
Level 2 variance	0.257***	$0.263^{***}$	0.266***	0.235***	$0.210^{***}$
Coefficients and stands slopes for the family-le	ard errors (in brackets). Noi	ne of them are significant so the cross-leve sted here	el interactions are not listed here.	For simplicity, the estimat	ted variance of the
* $p < .05$ , ** $p < .01$ ,	*** $p < .001$				

## 5 Conclusion

As outlined in the literature, the determinants of poverty are derived from individual, family, and social structures. However, most studies have used a single-level method and overlooked hierarchical structure, causing statistical and inferential problems (Chang 1992a; Leu 1995, 1996; Huang 2000; Hsueh 2002, 2004; Leu 2010b; Tsai 1994; Tsai and Huang 2007). We used HGLMs to analyze the determinants of poverty in Taiwan. The results demonstrated that poverty risks vary across regions. This implied that regional heterogeneity of poverty exists in Taiwan; thus, macro-level factors should be considered simultaneously when analyzing the effect of micro-level factors on poverty. Furthermore, governments should place poverty in a social context to develop strategies for poverty reduction that differ by region.

Some of the findings on the family-level factors corresponded with previous studies (Leu 1995, 1996; Huang 2000; Hsueh 2000, 2002, 2004). Education attainment, socioeconomic status, age, family type, dependency ratio, and number of earners were associated with poverty status. Human capital is crucial to improving the plight of the poor. Female-headed households exhibited higher risks of poverty than male-headed households did. Poverty among the elderly indicated that older adults are part of an economically disadvantaged group. Our study suggested that governments should focus on older adults and propose effective social policies to advance their economic security. All family types other than those without children were more likely to experience poverty than one-person families. Families with dependent children were more likely to experience poverty than families without children, implying that the burden of child rearing was associated with poverty. Children also tended to face higher risks of poverty, and child poverty has increased in Taiwan (Leu 2010a). As expected, the dependency ratio and number of earners affected poverty. According to Leu (1995), families with more earners are less likely to be poor, whereas a high dependency ratio is associated with a higher risk of poverty.

The results of several family-level characteristics did not correspond to the results of previous research (Chang and Huang 2013; Leu 1995; Chang 1992b). The relationship between household heads younger than 30 years old and poverty risk was unclear in this study. Fewer than 4 % of people who were household heads younger than 30 years old lived in poverty. Moreover, divorced families were not more likely to live in poverty than unmarried families. Married and widowed families were less likely to live in poverty, which might demonstrate that the burden of raising a family falls on unmarried people.

Significant relationships were observed between poverty and structural characteristics, including economic inequality, economic growth, structural transition, and labor market characteristics, when cross-level interactions were excluded. People living in regions with higher income inequality, greater spatial mismatch, and lower job quality were more likely to be poor. By contrast, people were less likely to live in poverty when the employment-to-population ratio and the ratio of employment in the service industry to employment in the manufacturing industry increased.

However, spatial mismatch did not increase the risk of poverty after cross-level interactions were introduced in Models 4–8. Studies have indicated that a service-to-manufacturing ratio was positively correlated with poverty (Tsai 1994, 1996; Kasarda 1993), but this study suggested that a service-to-manufacturing ratio decreased poverty. These unexpected findings implied that the effects of structural transition vary across countries. In Taiwan, low-paying and low-skilled jobs have increased in the service sector. For instance, the wholesale and retail trade sector, which is part of the service sector and does not require high-skilled jobs, has grown from 1787 to 2006 (DGBAS 2014). Studies have proved that service-sector expansion provides employment opportunities (Tseng et al. 2002). Hence, the expansion of the service sector helps the poor improve their economic circumstances.

The last part of the result referred to the random slopes at the family-level and the crosslevel interactions. The random coefficient model and the intercepts-as-outcomes model demonstrated that only the coefficient of the household dependency ratio varied randomly. Based on statistical theory, we introduced cross-level interaction terms between the dependency ratio and regional-level variables. The results indicated that no cross-level interactions were statistically significant. It was not proven that the effect of the dependency ratio on poverty was moderated by regional-level factors. Certain crucial variables related to family-level and regional-level factors were omitted because of data limitations, for example, attitudes and behaviors. The choice between a fixed and random slope is essential, but difficult. Selecting fixed or random slopes depends on theoretical considerations (Snijders and Bosker 1999).<sup>5</sup> Random slope estimates are less reliable than random intercept estimates, making it difficult to predict random slopes (Raudenbush and Bryk 2002).

Another possible reason for the non-significant cross-level effect is that the study included too few groups (23 groups), making the results less accurate. The power of a statistical test is related to the sample size (Mathieu et al. 2012; Moineddin et al. 2007). The power of a test relies on the total sample size at the lowest level, whereas the statistical power and cross-level interactions depend on the number of groups at the highest level (Hox 2010). Other factors, such as the magnitude of the cross-level interaction, the standard deviation of lower-level slopes, and the lower-level sample size also influence the power of a test (Mathieu et al. 2012). Thus, accurate estimates require a larger sample size at the highest level.

Despite these limitations, this study used an appropriate method to understand the determinants of poverty in Taiwan. In particular, the intercepts and slopes as outcomes models, which take account of cross-level interactions, accurately describe the status of poverty. The determinants of poverty consist of individual, family, and structural dimensions. Our results are encouraging and should be validated by future longitudinal data analysis. Future studies should also examine child poverty because according to our results, approximately 40 % of households with children live in poverty.

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<sup>&</sup>lt;sup>5</sup> See Raudenbush and Bryk (2002) and Snijders and Bosker (1999) for more detailed discussions on explanatory variable selection and the choice between a fixed and random slope.

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