Topics

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Intergenerational Income Mobility in Taiwan: Evidence from TS2SLS and Structural Quantile Regression

Abstract: We estimate intergenerational income mobility in Taiwan, employing repeated cross-sectional data. We find that the father–son, father–daughter, mother–son and mother–daughter income elasticities-at-40 are around 0.18, 0.23, 0.50 and 0.54, respectively. Moreover, the mother–child income elasticity increases slightly over children’s birth year, while the father–child elasticity is stable, but we do not find any time trend in elasticities. Since mean-regression results may not be informative in fast growing economies, we estimate *relative* mobility via structural quantile regression models. The results indicate that parents’ income affects children’s income mainly through the propagation of children’s income shocks, rather than affecting the level directly.

Keywords: intergenerational income mobility, structural quantile regression, two-sample two-stage least squares

JEL Classification: J62

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1 Introduction

This study investigates intergenerational income mobility in Taiwan. We measure how economic status is transmitted from one generation to the next. Interest in this correlation arises from the belief that low intergenerational income mobility implies the existence of inequality in opportunities in the society (Solon 1992), i.e., children from a poor family may have different

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opportunities for success than children from a rich family. Hence, an understanding of this correlation is necessary.

Intergenerational income mobility has been investigated since the 1970s. The seminal work of Becker and Tomes (1979) is among the first attempts by economists to analyze the intergenerational transmission of economic status. A common empirical approach to analyze intergenerational income mobility is to measure the elasticity of children's income with respect to parental income. A higher intergenerational income elasticity implies a lower degree of intergenerational income mobility. Earlier studies focus on estimating the intergenerational income elasticity within the United States and report the elasticity between fathers and sons as being quite low, see, e.g., Sewell and Hauser (1975), Bielby and Hauser (1977), and Behrman and Taubman's (1985). With improved estimation procedures, more recent studies for the case of the United States obtain higher estimates, see Solon (1992) and Zimmerman (1992), who correct for measurement error, and Haider and Solon (2006), Aaronson and Mazumder (2008), and Lee and Solon (2009), who correct for the life-cycle bias.

With the availability of new data, a growing body of research is now available to shed light on the intergenerational income elasticities for countries other than the United States. Studying the elasticity across countries makes comparisons among countries possible. As Solon (2002) points out, comparisons of intergenerational income mobility among countries may help us to understand how economic status is transmitted from one generation to the next and why the strength of intergenerational transmission varies across countries. The variation in the estimated elasticity across nations depends mainly on the differences in their education system or social policies (Blanden 2013) and the differences in the relationship between parents' and children's economic statuses (Bratsberg et al. 2007).

Existing international studies of intergenerational income elasticity seem to reach a consistent conclusion that the United States has a higher intergenerational income elasticity than other countries, implying a higher degree of inequality in opportunity across individuals. However, many of these studies do not account for measurement errors and life-cycle bias, rendering some of these results non-comparable.¹

In this study, we explore the case of Taiwan. Although research on intergenerational income mobility from various nations keeps growing, there exists little empirical evidence of the intergenerational income elasticity for the case of

¹ See Table 3 for a partial list of international studies, which use similar econometric specifications (i.e., the two-sample two-stage least squares regression method with children's age normalized) as the current study.

Taiwan. The case of Taiwan is interesting *per se* given the enormous social and economic changes (e.g., expansion in higher education and democratization) that the country underwent over the past two decades. In addition, our data allow us to study the relationships between parents and daughters and between mothers and children, which are rarely investigated by previous studies. This will shed more light on the context of intergenerational mobility.

In the empirical analysis, we employ the two-sample two-stage least squares (TS2SLS) estimator. This estimator allows us to account for measurement error and the sample selectivity arising from the use of co-residing of parent–child pairs in the estimation. In addition, since upward income mobility is prevalent in fast growing economies, results from mean-regression may not be very informative, we examine income mobility at different locations of the parent's and child's income distributions. This is accomplished by employing a structural quantile regression model with a TS2SLS procedure. Finally we also estimate the trends in intergenerational mobility across children's birth cohorts and over time.

Our estimation results show that the intergenerational income elasticities-at-40 are around 0.181 (between fathers and sons), 0.229 (between fathers and daughters), 0.501 (between mothers and sons), and 0.541 (between mothers and daughters), respectively. These estimates, especially that for fathers and sons, are smaller in magnitude compared with those obtained for other countries, e.g., the United States' 0.53 (Solon 1992), Brazil's 0.69 (Dunn 2007), Ecuador's 1.13 (Grawe 2004), Peru's 0.67 (Grawe 2004), Chile's 0.52–0.54 (Nunez and Miranda 2010), and China's 0.468, 0.419 and 0.567 (father–son, father–daughter, mother–son elasticities, respectively; see Gong, Leigh, and Meng 2012). Our mother–daughter elasticity estimate is higher than the 0.370 obtained by Gong, Leigh, and Meng (2012) for China though.² Our findings imply that there is a higher degree of intergenerational income mobility and, thus, a lower degree of inequality in economic opportunities when compared to other countries. The results of the structural quantile regression do not indicate a uniform relationship between parental income and children's income across their income distributions. In addition, we find that the intergenerational income elasticity has slightly increased over children's birth cohorts.

The remainder of this paper is organized as follows. We introduce our empirical framework and model specifications in Section 2. Section 3 describes the data and statistics. Section 4 presents our estimates of the intergenerational income elasticity and an international comparison. Finally, Section 5 contains concluding remarks.

2 All these studies use the TS2SLS regression for estimation.

2 Empirical strategy

2.1 Model specification

The relationship between a parent's and her child's income can be embodied in the following model.

$$\bar{y}_i^c = \bar{y}_i^p \rho + \varepsilon_i^c, \quad [1]$$

where $\bar{y}_i^c$ is a child in household i 's long-run income in log, $\bar{y}_i^p$ is that of her parent's, ρ is a measure of intergenerational income elasticity, and ε_i^c is an error term with variance $\sigma_{\varepsilon^c}^2$.

Using survey data for estimation, we do not have information on long-run income and estimating eq [1] is infeasible. Instead, following Solon's (1992) empirical model we proceed with a model of the relationship between long-run and short-run income.

$$y_{it}^c = \bar{y}_i^c + x_{it}^c \beta^c + v_{it}^c, \quad [2]$$

$$y_{it}^p = \bar{y}_i^p + x_{it}^p \beta^p + v_{it}^p, \quad [3]$$

where y_{it}^c and y_{it}^p are log income observed at a given point in time, x_{it}^c and x_{it}^p are their ages and age squared, and v_{it}^c and v_{it}^p are transitory shocks. Solving eqs. [2] and [3] for $\bar{y}_i^c$ and $\bar{y}_i^p$, we obtain the standard empirical model of intergenerational income mobility as

$$y_{it}^c = y_{it}^p \rho + x_{it}^c \beta^c + x_{it}^p \phi^c + \mu_{it}^c, \quad [4]$$

where $\mu_{it}^c = \varepsilon_i^c + v_{it}^c - v_{it}^p \rho$ and $\phi^c = -\rho \beta^p$. Equation [4] indicates that a child's current economic status is a function of her parent's current status and their ages (in quadratic form).

In estimating eq. [4] we normalize children's age to 40 and interact this normalized age with parental income in the estimation. This is to control for life-cycle bias arising from children's age profiles. By doing so, we obtain the intergenerational income elasticity-at-age-40. We also include children's and parents' birth cohort dummies and year dummies in the estimation equation to allow the average difference between the children's log income and their parents' log income to change across years for parent-child dyads belonging to different birth cohorts observed in different years.

Our parent-child pairs come from the Survey of Family Income and Expenditure (SFIE), which collects information on co-residing family members of a sampled household. The use of co-residing parent-child pairs may give rise

to selectivity bias. To correct for this potential bias, we use a TS2SLS estimator, and we supplement the SFIE data with the Manpower Utilization Survey (MUS) data.

With the TS2SLS estimator, we treat individuals in the MUS as “potential parents” and use the data to estimate a model for parents’ income.³

$$y_{jt} = q_j \delta + x_{40jt} \tilde{\beta}^p + x_{140kt}^p q_j \xi + v_{jt}, \quad [5]$$

where j indexes individuals in the MUS data and q_j denotes individual j ’s years of schooling, which is used as an instrument. The vector x_{40jt} includes individual j ’s age (centered at age 40) and its square. We control for the interaction term of age and her years of schooling (e.g., $x_{140kt}^p q_j$) in the equation as well. Estimation of eq. [5] yields estimates $\{\hat{\delta}, \hat{\beta}^p, \hat{\xi}\}$, which are used with data from the SFIE to generate imputed values of parents’ income at age 40 in the SFIE data.

$$\hat{y}_{kt}^p = q_k^p \hat{\delta} + x_{40kt}^p \hat{\beta}^p + x_{140kt}^p q_k^p \hat{\xi}, \quad [6]$$

where k indexes families in the SFIE. The imputed income $\hat{y}_{kt}^p$ is then used to obtain the residual $\hat{v}_{kt}^p$ of parents’ income. We replace v_{kt}^p by $\hat{v}_{kt}^p$ in estimating eq. [4]. Thus, we estimate eq. [4] via the control function approach. To account for sampling variation, which arises from our two-step estimation procedure, we obtain the standard errors of the parameter estimates by bootstrap with 1,000 replications.

It is noted that if parental education has a direct effect on children’s income status, the TS2SLS estimates will be upward biased. Since there is likely a direct effect of parents’ education on a child’s income, the TS2SLS estimates with parents’ education as an instrument represent an upper bound of the intergenerational income elasticity.

2.2 Quantile regression

In the literature of intergenerational income mobility, there are some studies exploring intergenerational income mobility at different locations of children’s income distribution using the quantile regression approach, e.g., Eide and Showalter (1999), Grawe (2004), Mocetti (2007), Bratberg, Nilsen, and Vaage (2007), and Ueda (2009). The reason is that yielding estimates of *relative* income

³ The term “potential parents” refers to individuals in the MUS data having similar characteristics (i.e., age and birth years) as parents in the SFIE data. We borrow this term from Nicoletti and Ermisch (2007).

mobility, quantile regression results are more informative than that of mean-regressions. This is especially so in fast growing economies, where absolute upward intergenerational income mobility is prevalent.

However, most of these studies focus on analyzing the mean effect of fathers' income. By focusing on the mean effect, they ignore the fact that at different locations of the parental income distribution, parents' income may have different effects on their children's income. Moreover, these studies do not account for measurement errors. Thus, in order to obtain a more complete picture of intergenerational income mobility for parents and children in different locations of their income distributions and obtain a richer set of results, in this study we consider a location-scale shift model (see Ma and Koenker 2006) as follows.

$$y_{kt}^c = x_{40kt}^c \beta^c + x_{kt}^p \phi^c + \sum_{b=1}^4 C_{bkt}^c \theta_b + \sum_{l=1}^4 C_{lkt}^p \zeta_l + \sum_t Y_t \eta_t \quad [7]$$

$$+ y_{kt}^p (\rho_1 + x_{40kt}^c \rho_2 + \mu_{kt}^c (\gamma + x_{40kt}^c \tau)), \text{ where } \mu_{kt}^c = v_{kt}^p \lambda + v_{kt}^c + \varepsilon_k^c,$$

$$y_{kt}^p = q_k^p \delta + x_{40kt}^p \beta^p + x_{140kt}^p q_k^p \xi + v_{kt}^p. \quad [8]$$

where $v_{kt}^p \sim F(0, \sigma_p^2)$ and $v_{kt}^c + \varepsilon_k^c \sim G(0, \sigma_c^2)$, respectively, are income shocks experienced by parents and children, x_{40kt}^c is a vector containing the age and its square centered at age 40 for a child in family k observed in year t , C_{bkt}^c and C_{lkt}^p are the dummy variables indicating whether or not a child and a parent in family k belong to birth cohort b and l , respectively, and Y_t is a year dummy indicating the year when income is observed. Again we normalize both parents' and children's ages to 40 and consider their interaction terms when estimating parents' and children's income equations.

It is shown by Ma and Koenker (2006) that recursive conditioning of eqs [7] and [8] yields

$$\begin{aligned} Q^c(\alpha^c | Q^p(\alpha^p | q_k^p, x_{40kt}^p), x_{40kt}^c, x_{kt}^p, C_{bkt}^c, C_{lkt}^p, Y_t) \\ = Q^p(\alpha^p | q_k^p, x_{40kt}^p) (\rho_1 + x_{40kt}^c \rho_2 + F^{-1}(\alpha^p) \lambda [\gamma + x_{40kt}^c \tau] + G^{-1}(\alpha^c) [\gamma + x_{40kt}^c \tau]) \\ + x_{40kt}^c \beta^c + x_{kt}^p \phi^c + \sum_{b=1}^4 C_{bkt}^c \theta_b + \sum_{l=1}^4 C_{lkt}^p \zeta_l + \sum_t Y_t \eta_t, \end{aligned} \quad [9]$$

$$Q^p(\alpha^p | q_k^p, x_{40kt}^p) = q_k^p \delta + x_{40kt}^p \beta^p + x_{140kt}^p q_k^p \xi + F^{-1}(\alpha^p), \quad [10]$$

where $Q^c(\alpha^c | \cdot)$ and $Q^p(\alpha^p | \cdot)$ are conditional quantile functions.

In this model, a parent's income exerts both a location and a scale effect on the income distribution of their children. That is, in addition to having a direct impact on the level of her child's income, a parent's income may also propagate

income shocks μ_{kt}^c . The direction and magnitude of parental income's level effect on her child's income depends on ρ_1 , while the propagation effect depends on the coefficients λ and γ . It is expected that ρ_1 , λ and γ are positive.

The estimation proceeds as follows. A first-stage regression model of “potential” parents' income is estimated based on the MUS data at different quantiles ($\alpha^p = 0.1, \dots, 0.9$). We then impute the term $F^{-1}(\alpha^p)$ using the SFIE data as follows.

$$\hat{v}_{kt}^p(\alpha^p) = y_{kt}^p - \hat{Q}^p(\alpha^p | q_k^p, x_{40kt}^p), \quad [11]$$

where $\hat{Q}^p(\alpha^p | q_k^p, x_{40kt}^p)$ is the imputed conditional quantile constructed using the MUS-based coefficient estimates with SFIE-based variables. Finally, we use the SFIE data to estimate eq. [9] with $F^{-1}(\alpha^p)$ replaced by $\hat{v}_{kt}^p(\alpha^p)$ at different quantiles $\{\alpha^p, \alpha^c\} = 0.1, \dots, 0.9$. This estimation procedure is the *control variate* approach proposed by Ma and Koenker's (2006) study.

The estimation of eq. [9] yields the intergenerational income elasticity estimate $\hat{\pi}(\alpha^p, \alpha^c) = \hat{\rho}_1 + x_{40kt}^c \hat{\rho}_2 + F^{-1}(\alpha^p) \hat{\lambda} [\hat{\gamma} + x_{40kt}^c \hat{\tau}] + G^{-1}(\alpha^c) [\hat{\gamma} + x_{40kt}^c \hat{\tau}]$, which measures the impact of parents' income-at-40 at quantile α^p on children's income-at-40 at quantile α^c . Thus, by employing Ma and Koenker's (2006) structural specification we obtain a richer set of results than those obtained by previous studies. Bootstrap with 1,000 replications is employed to obtain the standard errors of the parameter estimates.

2.3 Trend of the elasticity of intergenerational income mobility

There are also studies focusing on the changes in the intergenerational income elasticity over time. More specifically, researchers are attempting to discover whether changes in social policies or economic situation over time have an impact on this elasticity, because these policies or economic situation may have an influence on the costs and benefits of human capital investments and social demographic structures.

An important focus in the literature is related to education reforms or changes in governments' education policies. For example, extending the years of compulsory education (Pekkarinen, Uusitalo, and Kerr 2009), increasing the number of colleges and universities (Bratsberg et al. 2007), and increasing governmental spending on public education (Mayer and Lopoo 2004; Blanden 2011) will encourage the attendance of higher education and reduce gaps between children from high-income and children of low-income families. These in turn will enhance intergenerational income mobility. However, in

some circumstances, these reforms or policy changes may have the opposite effect according to the results in Mayer and Lopoo (2004), Blanden et al. (2004), Machin (2007) and Mocetti (2007). They argue that this is probably because of the following reasons.

1. Easier access to higher education may not increase the probability of being employed.
2. Labor market success is much more correlated with family background than academic performance.
3. College tuition and other fees may prevent low-income students from taking advantage of opportunities created by education reforms.

Changes in a society's demographic structure, e.g., increases in women's labor force participation rate or a decline in the marriage rate, will also affect the pattern of intergenerational income mobility. An increase in the female labor market participation rate or a delay in women's marriage age may enhance the importance of the mother in a family and strengthen the mother-child income correlation. See, for example, Mayer and Lopoo (2004) and Bratberg, Nilsen, and Vaage (2007) for a discussion.

Obviously, studying the variation in intergenerational income mobility over time or across children's birth cohorts will enable researchers to evaluate the impact of different factors on equality of economic opportunities. This will generate important policy implications for policy makers. However, up to now, the long-run trend in the intergenerational income elasticity and the factors affecting this trend are not nearly clear out yet.

The findings of the previous studies are mixed even for different studies of the same country. For case of the United States, see, for example, Fertig (2003/2004), Aaronson and Mazumder (2008), and Lee and Solon (2009). There are also studies for countries other than the United States: the United Kingdom (Nicoletti and Ermisch 2007; Blanden et al. 2004), and Australia (Leigh 2007). This is probably due, in part, to the differences in model settings, measurement, sample selections, and variable definitions among studies (Hertz 2007).

In this subsection we investigate whether and how intergenerational income mobility changes over time and across children's birth cohorts for the case of Taiwan. Our sample covers a period when the capacity of Taiwan's higher education expanded rapidly, and its labor market and family structure underwent radical changes. Our estimation strategy mainly follows that of Nicoletti and Ermisch (2007), Aaronson and Mazumder (2008) and Lee and Solon (2009).

We allow for non-linear cohort and year effects by interacting dummy variables indicating year when income is observed and children's birth cohort with parents' log income.

$$\begin{aligned}
 y_{kt}^c = & \sum_{b=1}^5 C_{bkt}^c y_{kt}^p \rho_{1b} + \sum_t Y_t y_{kt}^p \pi_{1t} + x_{40kt}^c y_{kt}^p \rho_2 + \sum_{b=1}^5 C_{bkt}^c \hat{v}_{kt}^p \tau_{1b} + \sum_t Y_t \hat{v}_{kt}^p \pi_{2t} \\
 & + x_{40kt}^c \hat{v}_{kt}^p \tau_2 + x_{40kt}^c \beta^c + x_{kt}^p \phi^c + \sum_{b=1}^4 C_{bkt}^c \theta_b + \sum_{l=1}^4 C_{lkt}^p \zeta_l + \sum_t Y_t \eta_t + v_{kt}^c,
 \end{aligned}
 \tag{12}$$

In eq. [12] we interact year dummies (denoted by Y_t) with parent's income to allow parental income to have different effects in different years when the incomes are observed. Thus, the coefficient π_{1t} measures intergenerational income elasticity for year t . We note that in estimating eq. [12] one of the year dummies interacted with parental income is excluded for identification and we choose to omit that for 1995. The coefficients for the cohort interaction term ρ_{1b} in eq. [12], therefore, measure the intergenerational income elasticity-at-40 for this omitted year. We also allow parental income to have different effects on children born in different cohorts by interacting parental income with cohort dummies (denoted by C_{bkt}^c). The coefficient ρ_{1b} captures intergenerational income elasticity for children belonging to cohort b . Moreover, $\rho_{1b} + \pi_{1t}$ is the intergenerational income elasticity for children belonging to cohort b in year t .

We control for cohort effects, year effects and life-cycle effects in eq. [12] by using cohort dummies for both generations (C_{bkt}^c and C_{lkt}^p), year dummies (Y_t), the parent's age in quadratic form (x_{kt}^p), and the normalized child's age in quadratic form (x_{40kt}^c , which is also interacted with parental income) as regressors. To control for potential bias arising from co-residence, we use the TS2SLS approach by incorporating a predicted error term ($\hat{v}_{kt}^p$), which is constructed using coefficients obtained by estimating a parental income equation with the MUS data, and its interactions with cohort dummies, the child's age, and parental income.

3 Data

We use two repeated cross-sectional datasets for estimation. The main dataset, where we obtain parent-child pairs, is from the SFIE. These parent-child pairs share the same residence. To correct for potential bias arising from using co-residing parent-child pairs, we follow the literature (see, e.g., Nicoletti and Ermisch 2007; Mocetti 2007) and employ the TS2SLS estimator with a supplementary dataset from the Manpower Utilization Survey (MUS). Details of the two datasets are given below. The way we use the two datasets are given in Section 2.

3.1 Survey of family income and expenditure

In our empirical work we combine two separate samples to estimate intergenerational economic mobility. Our main sample consists of repeated cross-sections taken from 1988 to 2006 SFIE.⁴ The SFIE has been conducted annually by the Directorate-General of Budget, Accounting and Statistics (DGBAS) since 1976. The purpose of the survey is for the government to understand income distribution, savings behavior, and expenditure pattern of households in Taiwan. Each year a nationally representative sample of roughly 14,000 households are interviewed. It collects rich information on a sampled household (e.g., housing, assets, expenditure on different items, stocks of household appliances) and each of its members (e.g., employment status and incomes, relationship with the household head). We follow the literature by focusing on earned income, i.e., wages, salaries, and business and farm income. Thus, only individuals who had positive labor income are included in our sample.

In order to construct reliable measures of the intergenerational income elasticity, we impose two sample selection rules. Firstly, we include only adult children aged 26–45 who have parents aged 41–64. This reduces life-cycle bias. Secondly, we exclude a household if the difference between a parent and her child's age is less than 15. This avoids the possibility of misreporting of age or relationship among household members. After all these exclusions, we have 17,424 father–son pairs, 5,793 father–daughter, 8,014 mother–son, and 2,952 mother–daughter pairs during the period 1988–2006. All these parent–child dyads co-resided.

To have a preliminary examination of the intergenerational correlation in income and income distribution in our SFIE sample, we look at the scatter plots in Figure 1, where the line in each graph is a regression line produced by the nonparametric method of local linear regression (see Fan and Gijbels 1996). We see in the graphs that regression lines for mothers are steeper, suggesting a larger impact of mothers' income on children's income. Moreover, mothers' income is less dispersed than fathers' and daughters' income is also less dispersed than sons' income.

3.2 Manpower utilization survey

Adopting the TS2SLS to correct for potential bias arising from using co-residing parent–child dyads, we use the data from 1978 to 1988 MUS for the first-stage regression to estimate a model of parents' income. The coefficient estimates obtained from the first-stage regression are used to predict parents' income using the SFIE data. The predicted parental income is used in the second-stage regression with the SFIE data.

⁴ The survey did not collect information on relations among individuals in a household prior to the 1988 wave. For the post-2007 surveys, information on individual income is not release.

Figure 1: Income distribution

The MUS was first conducted in 1962 by the Taiwan Provincial Department of Social Affairs. The task was taken over by the DGBAS since 1977. The survey is for the government to understand the labor market (e.g., unemployment, growth in wages/salaries, distribution of employment in different industries/occupation). Each year, a random sample of households is drawn and all individuals aged 15 and over in a sampled household are interviewed. The survey collects information on individuals’ labor income and demographic characteristics (i.e., gender, age and education). Thus, data from the MUS are repeated cross-sectional.

Since parents in the SFIE sample were 41–64 years old during 1988–2006 (i.e., born during 1924–1965), we use the 1978–1988 waves of the MUS and include individuals aged 31–55 (born during 1923–1957) in our sample. These individuals are used as “potential parents” for the SFIE children. After excluding individuals who were unemployed or no earned income at the time of survey, we have a total of 105,511 “potential fathers” with an average age of 42 and 33,429 “potential mothers” with an average age of 41.⁵ Descriptive statistics of our SFIE and MUS samples are reported in Table 1.

⁵ These individuals may or may not be co-residing with their children at the time of the survey. Their co-residence rates is 48.38%.

Table 1: Descriptive statistics: SFIE (1988–2006) and MUS (1978–1988)

Variables	Mean (standard deviation) and [minimum, maximum]			
	Sons	Daughters	Fathers	Mothers
SFIE				
Earned income	375,736.016 (181,516.426)	332,471.226 (168,417.844)	394,808.406 (370,205.244)	268,840.888 (229,810.912)
Log earned income	[2,360.000 2.950e + 06] 12.727 (0.487)	[8,638.000 5.000e + 06] 12.602 (0.483)	[500.000 8.000e + 06] 12.459 (1.058)	[930.000 3.000e + 06] 12.167 (0.913)
Age	[7.766 14.897] 29.931 (3.498)	[9.064 15.425] 28.711 (2.912)	[6.215 15.895] 56.930 (4.127)	[6.835 14.914] 53.890 (4.718)
Years of schooling	[26.000 45.000] 11.790 (2.781)	[26.000 45.000] 13.269 (2.427)	[42.000 64.000] 6.986 (4.123)	[41.000 64.000] 5.341 (4.301)
Observations	[0.000 18.000] 22,106	[0.000 18.000] 7,475	[0.000 18.000] 18,072	[0.000 18.000] 8,725
MUS				
Earned income			168,238.875 (113,390.302)	107,441.004 (76,994.016)
Log earned income			[120.000 1.200e + 06] 11.839	[600.000 1.200e + 06] 11.360
Age			[4.787 13.998] (0.651)	[6.397 13.998] (0.709)
Schooling years			41.974 (7.258)	40.525 (6.779)
Observations			[31.000 55.000] 7.899 (3.955)	[31.000 55.000] 6.521 (4.602)
			[0.000 18.000] 105,511	[0.000 18.000] 33,429

4 Empirical results

4.1 Baseline results

In this section we describe estimates of the intergenerational income elasticity-at-40 for father–son, father–daughter, mother–son, and mother–daughter relations using information from the SFIE and the MUS data. The results from estimating eq. [4] are reported in Table 2. The income elasticity estimates are 0.181, 0.229, 0.501, and 0.541 for the father–son, father–daughter, mother–son, and mother–daughter pairs, respectively. All the coefficients are statistically significant at conventional levels, except for the father–daughter elasticity.

Table 2: Intergenerational income elasticity-at-40

Variables	Father– Son	Father– Daughter	Mother– Son	Mother– Daughter
Parental income	0.181*** (0.066)	0.229 (0.161)	0.501*** (0.103)	0.541*** (0.164)
(Children’s age – 40) *	–0.026* (0.015)	–0.051 (0.032)	0.036 (0.025)	0.003 (0.033)
(Children’s age – 40) ² *	–0.002** (0.001)	–0.003* (0.002)	0.001 (0.001)	–0.001 (0.002)
Residuals	–0.203*** (0.071)	–0.094 (0.175)	–0.483*** (0.119)	–0.423** (0.202)
(Children’s Age – 40) *	0.022 (0.016)	0.067* (0.035)	–0.041 (0.029)	–0.003 (0.042)
(Children’s Age – 40) ² *	0.002** (0.001)	0.004** (0.002)	–0.001 (0.002)	0.001 (0.002)
Residuals	0.287* (0.165)	0.576 (0.368)	–0.406 (0.274)	–0.039 (0.368)
(Children’s Age – 40) ²	0.022** (0.009)	0.034* (0.018)	–0.015 (0.015)	0.007 (0.020)
Parent’s age	0.035* (0.021)	–0.037 (0.029)	–0.026 (0.021)	–0.005 (0.034)
Parent’s age squared	–0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Children’s birth cohort dummies	Yes	Yes	Yes	Yes
Parent’s birth cohort dummies	Yes	Yes	Yes	Yes
Year dummies	Yes	Yes	Yes	Yes
Observation	17,424	5,793	8,014	2,952

Notes: [†]Standard errors are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

The impact of mothers' income on children's economic status appears to be more important than the impact of fathers' income status. This may arise from the fact that mothers, relative to fathers, play a more important role in taking care of their children especially during the children's infancy and early childhood, which is a critical period for cognitive development. In addition, the parent–daughter elasticities appear to be slightly higher than the parent–son elasticities.

It is useful to compare our estimates with those for other countries in order to gauge the degree of intergenerational income mobility in Taiwan. Table 3 summarizes estimates of intergenerational income elasticity obtained for different countries based on TS2SLS. We focus on the father–son income elasticity here because most previous studies obtain only father–son elasticity estimates. The comparison between our estimates with those obtained for other countries indicate that the Taiwan's intergenerational income elasticity is at the low end of the spectrum.

Moreover, to our knowledge, among previous studies only Gong, Leigh, and Meng (2012) obtains estimates of mother–child income elasticities. Consistent with our results, based on working parents and children, its mother–son income elasticity estimate (0.567) is larger than the father–son income elasticity estimate (0.468). Its mother–daughter estimate (0.370) is lower than other estimates though.

4.2 Quantile regression results

We next discuss the results in Tables 4–7, which are obtained from estimating the structural quantile regression model [9]. We plot the estimates in Figure 2 to enable visualization. In the estimation ages of both the parent and the child are normalized to 40 so that the estimates represent the impact of a 40-year-old parent's income on her child's income at age 40.

We first look at the father–son elasticity estimates. The results in Table 4 suggest that fathers' income, across all quantiles, has the highest impact on sons whose income is at the median of the income distribution. The exception is for fathers who are at the 90th quantile, where the largest effect happens when sons' income at the 0.1 quantile. For fathers whose income is at the 0.1 to 0.9 quantiles, the intergenerational income elasticities are in the range of 0.183–0.209 for sons at the median of their income distribution, and these estimates do not vary very much with father's income quantile. These estimates are close to the baseline estimate of 0.181 reported in Table 2.

Table 3: International evidence on intergenerational income elasticity based on TS2SLS

Country	Source	Children's Age	Parents' Age	Father– Son	Father– Daughter	Mother– Son	Mother– Daughter
Brazil	Dunn (2007)	25–34	30–50 (in 1976)	0.69			
Chile	Contreras, Fuenzalida, and Nunez (2006)	23–55	N.A.	0.58–0.67			
China	Nunez and Miranda (2010)	25–40	15–55	0.57–0.74			
Ecuador	Gong, Leigh and Meng (2012) [†]	17–41	37–60	0.468	0.419	0.567	0.370
France	Grawe (2004)	24–40	45–60	1.13			
Italy	Lefranc and Tranoy (2005)	30–40	55–70	0.42–0.50	0.15–0.42		
Japan	Mocetti (2007)	30–45	30–50	0.44			
Malaysia	Ueda [‡] (2009)	20–64	41–88	0.46	0.38		
Nepal	Grawe (2004)	> =23	24–59	0.54			
Pakistan	Grawe (2004)	24–40	45–60	0.32			
Peru	Grawe (2004)	25–35	45–60	0.24			
Taiwan	Grawe (2004)	24–40	45–60	0.67			
United States	This study	26–45	41–64	0.181	0.229	0.501	0.541
	Björklund and Jäntti (1997)	28–36	Mean: 45	0.52			
	Grawe (2004)	28–41	Mean: 40.2	0.47			

Notes: [†]Total parental income was used in estimation.
[‡]Child and parent are both working.

Table 4: Quantile regression results – Father–son elasticities

		Son's income quantile α^c								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
Father's Income Quantile α^p	0.1	0.120 (0.113)	0.159** (0.074)	0.122* (0.065)	0.102 (0.070)	0.200*** (0.059)	0.170*** (0.065)	0.138** (0.064)	0.094 (0.068)	0.055 (0.144)
	0.2	0.132 (0.116)	0.170** (0.076)	0.111 (0.071)	0.103 (0.073)	0.200*** (0.064)	0.164** (0.073)	0.132** (0.065)	0.082 (0.073)	-0.026 (0.159)
	0.3	0.137 (0.120)	0.175** (0.083)	0.116 (0.072)	0.106 (0.074)	0.199*** (0.075)	0.158** (0.073)	0.120* (0.068)	0.082 (0.075)	-0.028 (0.166)
	0.4	0.132 (0.118)	0.169** (0.077)	0.114 (0.071)	0.102 (0.071)	0.192*** (0.068)	0.156** (0.073)	0.120* (0.067)	0.081 (0.071)	-0.028 (0.162)
	0.5	0.120 (0.114)	0.183** (0.074)	0.112* (0.065)	0.101 (0.069)	0.193*** (0.062)	0.169** (0.067)	0.117* (0.064)	0.078 (0.069)	0.020 (0.151)
	0.6	0.145 (0.128)	0.181** (0.080)	0.113 (0.070)	0.101 (0.075)	0.193*** (0.068)	0.151** (0.073)	0.117* (0.065)	0.074 (0.074)	-0.036 (0.165)
	0.7	0.173 (0.126)	0.181** (0.082)	0.120 (0.077)	0.093 (0.075)	0.192*** (0.073)	0.154* (0.079)	0.115 (0.070)	0.075 (0.073)	-0.046 (0.176)
	0.8	0.176 (0.124)	0.181** (0.085)	0.111 (0.074)	0.086 (0.077)	0.183** (0.073)	0.127 (0.078)	0.109 (0.071)	0.068 (0.077)	-0.043 (0.177)
	0.9	0.229* (0.134)	0.216** (0.094)	0.122 (0.083)	0.087 (0.081)	0.209*** (0.078)	0.126 (0.089)	0.107 (0.076)	0.043 (0.086)	-0.103 (0.202)

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 5: Quantile regression results – Father–daughter elasticities

Father's Income Quantile α^p	Daughter's income quantile α^c								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	-0.042 (0.293)	0.088 (0.210)	0.165 (0.165)	0.151 (0.180)	0.304 (0.206)	0.336 (0.226)	0.064 (0.258)	-0.050 (0.297)	0.167 (0.226)
0.2	-0.062 (0.309)	0.092 (0.228)	0.167 (0.172)	0.170 (0.181)	0.293 (0.223)	0.341 (0.257)	0.007 (0.284)	-0.071 (0.293)	0.167 (0.248)
0.3	-0.075 (0.299)	0.101 (0.228)	0.169 (0.168)	0.177 (0.190)	0.266 (0.229)	0.333 (0.277)	-0.027 (0.304)	-0.057 (0.314)	0.137 (0.253)
0.4	-0.072 (0.285)	0.102 (0.240)	0.159 (0.178)	0.163 (0.178)	0.271 (0.230)	0.338 (0.265)	-0.027 (0.285)	-0.067 (0.319)	0.142 (0.248)
0.5	-0.064 (0.296)	0.089 (0.220)	0.135 (0.280)	0.148 (0.180)	0.291 (0.208)	0.336 (0.256)	0.050 (0.270)	-0.062 (0.296)	0.172 (0.236)
0.6	-0.089 (0.312)	0.110 (0.233)	0.153 (0.180)	0.167 (0.196)	0.266 (0.231)	0.329 (0.287)	-0.017 (0.298)	-0.097 (0.312)	0.151 (0.259)
0.7	-0.096 (0.328)	0.110 (0.241)	0.132 (0.185)	0.172 (0.212)	0.279 (0.234)	0.345 (0.306)	-0.007 (0.299)	-0.129 (0.336)	0.126 (0.267)
0.8	-0.101 (0.315)	0.117 (0.243)	0.130 (0.184)	0.171 (0.203)	0.272 (0.247)	0.350 (0.321)	-0.017 (0.318)	-0.120 (0.345)	0.132 (0.265)
0.9	-0.102 (0.343)	0.101 (0.260)	0.197 (0.210)	0.171 (0.243)	0.277 (0.268)	0.342 (0.329)	0.018 (0.329)	-0.190 (0.364)	0.160 (0.309)

Table 6: Quantile regression results – Mother–son elasticities

Mother's Income Quantile α^p		Son's income quantile α^c								
		0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	0.324	0.268	0.233	0.225**	0.335***	0.355***	0.361***	0.337**	0.569***	
	(0.217)	(0.198)	(0.154)	(0.107)	(0.096)	(0.107)	(0.119)	(0.139)	(0.141)	
0.2	0.327	0.253	0.222	0.231**	0.307***	0.319***	0.329**	0.312**	0.513***	
	(0.222)	(0.205)	(0.152)	(0.110)	(0.096)	(0.111)	(0.128)	(0.138)	(0.144)	
0.3	0.316*	0.288	0.303**	0.231**	0.343***	0.338***	0.370***	0.366***	0.469***	
	(0.191)	(0.180)	(0.130)	(0.094)	(0.079)	(0.088)	(0.105)	(0.130)	(0.122)	
0.4	0.322*	0.281	0.306**	0.236**	0.344***	0.337***	0.362***	0.383***	0.482***	
	(0.195)	(0.183)	(0.129)	(0.095)	(0.085)	(0.091)	(0.104)	(0.140)	(0.123)	
0.5	0.294*	0.306*	0.298**	0.219**	0.305***	0.330***	0.355***	0.389***	0.436***	
	(0.169)	(0.164)	(0.119)	(0.086)	(0.075)	(0.079)	(0.100)	(0.123)	(0.107)	
0.6	0.306*	0.316*	0.301**	0.230**	0.336***	0.330***	0.359***	0.388***	0.464***	
	(0.183)	(0.175)	(0.127)	(0.095)	(0.082)	(0.089)	(0.104)	(0.133)	(0.116)	
0.7	0.300*	0.331**	0.299**	0.225**	0.325***	0.321***	0.351***	0.391***	0.444***	
	(0.179)	(0.165)	(0.124)	(0.092)	(0.078)	(0.083)	(0.099)	(0.128)	(0.115)	
0.8	0.290*	0.320**	0.292***	0.218***	0.303***	0.317***	0.342***	0.390***	0.420***	
	(0.174)	(0.159)	(0.110)	(0.084)	(0.076)	(0.080)	(0.093)	(0.121)	(0.108)	
0.9	0.285*	0.311**	0.278**	0.207***	0.294***	0.326***	0.347***	0.381***	0.398***	
	(0.161)	(0.156)	(0.108)	(0.077)	(0.069)	(0.071)	(0.089)	(0.112)	(0.098)	

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Table 7: Quantile regression results – Mother–daughter elasticities

Mother's Income Quantile α^p	Daughter's income quantile α^c								
	0.1	0.2	0.3	0.4	0.5	0.6	0.7	0.8	0.9
0.1	0.193 (0.374)	0.312 (0.269)	0.402 (0.258)	0.418 (0.336)	0.259 (0.351)	0.508* (0.307)	0.373 (0.255)	0.476 (0.402)	0.756* (0.413)
0.2	0.246 (0.386)	0.323 (0.280)	0.422 (0.278)	0.346 (0.335)	0.237 (0.356)	0.274 (0.325)	0.332 (0.261)	0.461 (0.398)	0.767* (0.440)
0.3	0.167 (0.327)	0.281 (0.242)	0.341 (0.239)	0.426 (0.286)	0.336 (0.282)	0.447* (0.256)	0.368 (0.236)	0.576* (0.321)	0.698** (0.332)
0.4	0.104 (0.365)	0.288 (0.254)	0.364 (0.248)	0.437 (0.279)	0.407 (0.289)	0.443* (0.268)	0.422* (0.226)	0.603* (0.332)	0.677** (0.343)
0.5	0.150 (0.303)	0.281 (0.220)	0.306 (0.211)	0.426* (0.234)	0.389 (0.257)	0.446* (0.233)	0.350* (0.211)	0.535* (0.287)	0.648** (0.280)
0.6	0.133 (0.350)	0.250 (0.249)	0.344 (0.229)	0.400 (0.268)	0.361 (0.290)	0.455* (0.264)	0.383* (0.220)	0.566* (0.309)	0.660** (0.300)
0.7	0.144 (0.338)	0.267 (0.227)	0.328 (0.210)	0.408 (0.263)	0.364 (0.264)	0.443* (0.255)	0.370 (0.229)	0.555* (0.309)	0.643** (0.306)
0.8	0.168 (0.318)	0.270 (0.218)	0.311 (0.205)	0.428* (0.244)	0.395 (0.251)	0.419* (0.236)	0.358* (0.204)	0.522* (0.281)	0.622** (0.276)
0.9	0.198 (0.294)	0.248 (0.202)	0.289 (0.186)	0.398* (0.220)	0.363 (0.228)	0.413* (0.223)	0.328 (0.203)	0.554** (0.257)	0.613** (0.252)

Note: *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

Figure 2: Quantile regression results

Moreover, fathers' income across different quantiles does not have a statistically significant impact on sons who are at the 0.1 income quantile (except when fathers' income is at the 0.9 quantile) or the 0.8 and 0.9 quantiles. In other words, sons with very low or very high income are unlikely to be affected by their fathers. This implies that father's income has no effect on his son's income if the latter has experienced a large (either positive or negative) income shock, which put him in the upper or lower end of the income distribution.

For the very low-income sons (i.e., at income quantiles 0.1 and 0.2), intergenerational income elasticity's magnitude increases with their fathers' income quantile. The estimates are statistically insignificant for fathers at the 0.1–0.8 income quantiles though. This implies that higher income fathers have a greater beneficial influence on their low-income sons. This pattern is reversed for sons at the 0.6 and 0.7 income quantiles. For these sons, the impact of fathers' income decreases with the quantile of fathers' income.

Overall, the father–son income elasticity estimates from the structural quantile regression model suggest that intergenerational father–son income mobility is the highest (i.e., elasticity is the lowest) among high income sons (at quantiles 0.7–0.9) and very low-income sons (at quantile 0.1). This implies a healthy

pattern of social mobility. However, very high income fathers (i.e., at income quantile 0.9) do have a larger positive impact on their low-income sons who are at the 0.1 and 0.2 income quantiles. Moreover, the lack of a systematic pattern of the elasticity estimates at different income quantiles of fathers implies that the level effect, as embodied by the coefficient ρ_1 in eq. [9], is not strong.

Consistent with the baseline estimate for the father–daughter elasticity, the quantile regression estimates are all statistically insignificant at conventional levels (see Table 5). Given these imprecise estimates, we are not able to draw conclusions on the father–daughter income mobility.

The mother–son income elasticity estimates reported in Table 6 exhibit an interesting pattern, which is very different from that for the father–son estimates. The mother–son income elasticity increases almost monotonically with sons' income quantile, while there is not very much variation in the elasticity at different quantiles of mothers' income distribution. In other words, mothers' income has more influence on sons who have higher income and this influence is quite uniform across mothers of different income. This suggests mothers' income enlarges the income shocks experienced by sons. Moreover, the mild variation in the elasticity estimates across mothers' income quantiles implies that the level effect of mothers' income is not large.

The mother–daughter income elasticity estimates are reported in Table 7. In general, the estimates are large, especially for higher income daughters. The estimates are mostly statistically significant at conventional levels for daughters whose income is at the 0.6–0.9 quantiles. As for the variation of the estimates at different quantiles of mothers' income distribution, we do not find a systematic pattern. This suggests that higher income daughters benefit from an increase in their mothers' income. This indicates that while there is a low degree of income mobility for higher income mothers (above the median), there is a high degree of income mobility among lower income daughters (at the 0.5 quantile or below). Moreover, similar to findings implied by the father–son, mother–son, and father–daughter results, we do not find a strong level effect of mothers' income on daughters' income.

In summary, an increase in a father's income raises his son's income especially when the son's income is at the median, while having no effect on daughters' income at all. Mothers' income has a positive effect on higher income daughters or sons, while having no statistically significant effect on lower income children. Moreover, parental income is likely to have only a scale effect (i.e., propagation of income shocks) and it does not have a level (i.e., location) effect.

4.3 Non-linear trends

To explore the variation in the impact of parental income on children's economic status across children's birth cohorts and over time, we estimate model [12], which allows the intergenerational income elasticity to follow a non-linear time trend and a non-linear child-birth-cohort trend. The results are reported in Table 8.⁶ We can obtain the cohort b elasticity in year t through the summation $\rho_{1b} + \pi_{1t}$. Moreover, a cohort b elasticity for the whole sample period Π_b can be obtained by adding the average year coefficients $\frac{1}{19} \sum_{t=1988}^{2006} \pi_{1t}$ to ρ_{1b} . Similarly, a year t elasticity for all cohorts Φ_t can be obtained by adding the average cohort coefficients $\frac{1}{5} \sum_{b=1}^5 \rho_{1b}$ to π_{1t} .

The estimates of cohort-specific intergenerational income elasticity Π_b are plotted in Figure 3. The graphs in Figure 3 suggest that the father–daughter income elasticity seems to increase with daughters' birth year, but the estimates are mostly statistically insignificant at conventional levels, while the father–son income elasticity is flat over son's birth years. By contrast, the effect of mothers' income on their children's income increases over the year of birth of the children. This implies income mobility between mothers and their children is lower for children who were born later. The contrast in the mother–child and father–child correlations in income is interesting. It suggests an increasingly important role of a mother in the formation of her children's human capital. The increase in the social and economic influence of the mother in a family can be explained by the rapid increase in women's labor market participation rate and education attainment in Taiwan, where the women's labor market participation rate increased from 1978s 39.13% to 1988s 45.56% and to 2011s 49.97%, and the ratio of women obtaining a bachelor's degree also increased from 1979s 37.54% to 2005s 51.48%.

Now we turn to the trend in the intergenerational income elasticity across observation years as reported in Figure 4. The graphs in Figure 4 indicate that there does not exist a clear upward or downward trend for the estimates of the intergenerational income elasticity. This suggests that the pattern of intergenerational income mobility roughly stays constant over time.

Taken together, our results suggest that while there is an increase in the impact of mothers' income on their children's income over these children's birth years, the father–child income correlation does not vary systematically across

⁶ Given that the interaction term involving the 1995 year dummy and parental income is excluded in the estimation for identification, the coefficient ρ_{1b} represents intergenerational income elasticity for 1995.

Table 8: Nonlinear cohort-year trend in intergenerational income elasticity-at-40

Variables	Father– Son	Father– Daughter	Mother– Son	Mother– Daughter
Parental Income * Children's Birth Cohort				
(Children's Birth Cohort 1943–1959)	0.186** (0.080)	0.196 (0.184)	0.452*** (0.138)	0.235 (0.231)
(Children's Birth Cohort 1960–1963)	0.222** (0.089)	0.176 (0.202)	0.697*** (0.156)	0.600** (0.254)
(Children's Birth Cohort 1964–1969)	0.206** (0.105)	0.250 (0.220)	0.713*** (0.181)	0.833*** (0.272)
(Children's Birth Cohort 1970–1974)	0.243* (0.133)	0.359 (0.261)	0.830*** (0.233)	0.926*** (0.342)
(Children's Birth Cohort 1975–1980)	0.216 (0.159)	0.387 (0.306)	0.935*** (0.279)	0.856** (0.399)
Parental Income * Year				
Year 1988	0.024 (0.078)	0.139 (0.134)	0.100 (0.146)	0.278 (0.205)
Year 1989	0.022 (0.075)	0.209 (0.135)	0.000 (0.136)	0.252 (0.214)
Year 1990	–0.093 (0.071)	0.079 (0.112)	0.196* (0.115)	0.150 (0.186)
Year 1991	–0.014 (0.060)	0.063 (0.098)	0.146 (0.109)	0.213 (0.167)
Year 1992	–0.063 (0.061)	0.250*** (0.095)	0.092 (0.110)	0.270* (0.161)
Year 1993	–0.011 (0.064)	0.156 (0.110)	–0.143 (0.109)	0.095 (0.135)
Year 1994	–0.032 (0.059)	0.106 (0.096)	–0.080 (0.102)	0.225 (0.138)
Year 1995	– –	– –	– –	– –
Year 1996	–0.019 (0.067)	–0.047 (0.106)	0.010 (0.109)	0.045 (0.155)
Year 1997	–0.017 (0.062)	–0.029 (0.099)	0.009 (0.111)	–0.050 (0.168)
Year 1998	0.007 (0.067)	–0.041 (0.102)	–0.021 (0.108)	0.042 (0.163)
Year 1999	–0.068 (0.066)	–0.029 (0.112)	–0.099 (0.108)	0.087 (0.167)
Year 2000	0.004 (0.080)	–0.098 (0.118)	–0.191 (0.123)	–0.051 (0.169)
Year 2001	–0.010 (0.081)	–0.024 (0.124)	–0.135 (0.138)	–0.061 (0.188)

(continued)

Table 8: (Continued)

Variables	Father– Son	Father– Daughter	Mother– Son	Mother– Daughter
Year 2002	0.066 (0.082)	0.093 (0.148)	0.027 (0.141)	–0.088 (0.202)
Year 2003	0.070 (0.088)	0.009 (0.146)	–0.095 (0.148)	–0.007 (0.209)
Year 2004	0.033 (0.091)	0.099 (0.154)	0.008 (0.161)	0.108 (0.219)
Year 2005	0.003 (0.096)	–0.083 (0.151)	–0.139 (0.156)	–0.005 (0.218)
Year 2006	0.046 (0.104)	–0.039 (0.158)	–0.129 (0.156)	0.151 (0.223)
(Children's Age – 40) * (Parental Income)	–0.021 (0.015)	–0.047 (0.035)	0.059** (0.027)	0.051 (0.039)
(Children's Age – 40) ² * (Parental Income)	–0.002** (0.001)	–0.003** (0.002)	0.001 (0.001)	0.001 (0.002)
(Children's Age – 40)	0.240 (0.175)	0.529 (0.405)	–0.661** (0.298)	–0.584 (0.429)
(Children's Age – 40) ²	0.020** (0.009)	0.039** (0.019)	–0.017 (0.015)	–0.010 (0.021)
Parent's Age	0.028 (0.021)	–0.040 (0.029)	–0.030 (0.022)	–0.001 (0.036)
Parent's Age Squared	–0.000 (0.000)	0.000* (0.000)	0.000 (0.000)	0.000 (0.000)
Residuals * Children's Birth Cohort	Yes	Yes	Yes	Yes
Residuals * Year	Yes	Yes	Yes	Yes
Residuals * Children Age Centered at 40	Yes	Yes	Yes	Yes
Children's Birth Cohort Dummies	Yes	Yes	Yes	Yes
Parent's Birth Cohort Dummies	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes
Observation	17,424	5,793	8,014	2,952

Note: Standard errors are in parentheses. *, ** and *** denote statistical significance at the 10%, 5% and 1% levels, respectively.

children's birth years. Moreover, there does not exist a clear pattern over time for the intergenerational income elasticity.

The lack of a downward trend for the parent–child income elasticity across children's birth cohorts and for the parent–child income elasticity over time is surprising given that there was a significant expansion of the higher education system starting from the early 1990s. The number of four year colleges increased

Figure 3: Cohort trend

Figure 4: Year trend

from 46 in 1990 to 147 in 2006 and the number of college graduates increased from 49,399 in 1990 to 228,645 in 2006. An expansion of higher education is expected to have increased education opportunities for all children regardless of their family background such that it should reduce the impact of parents' economic status on children's income.

The lack of a downward trend for intergenerational income elasticity in spite of a higher education expansion may be due to the fact that while more education opportunities lower the costs for some children to obtain more education, an additional year of schooling may not translate into labor market success for low-income children. This is because labor market success is likely to be strongly related to parents' socioeconomic characteristics. Moreover, tuition and other fees associated with attending college may also prevent some low-income families' children from enjoying the expanded education opportunities. See, for example, Blanden et al. (2004) and Machin (2007) for the case of the United Kingdom and Mocetti (2007) for the case of Italy, where an expansion of higher education did not boost intergenerational income mobility.

5 Conclusion and discussion

We use data from 1988 to 2006 Survey of Family Income and Expenditures and 1978 to 1988 Manpower Utilization Survey to explore the father–son, father–daughter, mother–son and mother–daughter income elasticities. In order to control for the measurement errors and mitigate sample selectivity arising from using co-residing parents and children, we employ the TS2SLS regression estimator for our empirical analysis. Moreover, we also estimate parental income's distributional effects by means of a structural quantile regression model.

The degree of the mother–child income elasticity is higher than the father–child elasticity. Moreover, the magnitude of the mother–child income elasticity is slightly higher (i.e., less mobile) for daughters than for sons. Our estimation results also suggest that Taiwan's intergenerational income elasticity is low compared with other countries.

Furthermore, our structural quantile regression estimation results indicate a non-uniform degree of intergenerational income mobility across both parents' and children's income distributions. The results also imply that parental income affects children's income mainly through the propagation of income shocks experienced by children, rather than a direct effect on the level.

Finally, the key finding from estimating the trends of the intergenerational income elasticity is that the mother–child income elasticity increased over

children's birth years. This reflects the rise of mothers' influence on children's economic status, possibly as a result of a rise in their education attainment and labor market participation over the past few decades. However, we do not find the trends in the father-child income elasticity over children's birth years or the parent-child income elasticity across the years when income is observed. This indicates an absence of an effect of Taiwan's higher education expansion since the early 1990s.

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