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INTERGENERATIONAL ECONOMIC MOBILITY AROUND THE WORLD

Intergenerational Income Mobility in Singapore

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Intergenerational Income Mobility in Singapore*

Irene Ng

Abstract

Research on intergenerational earnings mobility in less developed economies is lacking. This paper investigates the case of Singapore, a newly-industrialized economy in Asia. Interval regressions are employed because of grouped dependent variables. Instrumental variables address problems of respondent errors and unobserved permanent income. Still, the estimated intergenerational elasticity of between 0.23 and 0.28 is probably under-estimated because the study uses a survey of young respondents who reported contemporaneous incomes of parents. Transformation of the estimates using scales in recent comparative studies indicates that intergenerational earnings mobility in Singapore may be moderately low when compared internationally. Education as a means through which parents invest in their children's future earnings appears important. There are some small independent returns from schooling. Mobility does not appear to differ by ethnicity, sex or income. These findings have important implications for equity, development and policy in Singapore, which has rising income disparity, a maturing economy, and an educational system which is increasingly privately run.

KEYWORDS: intergenerational income mobility, Singapore, education, inequality

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1. INTRODUCTION

While the literature on intergenerational income mobility has advanced beyond simple measurement to comparative studies over time, space and educational regimes, estimation of mobility in less advanced countries remains lacking. These studies include Lillard and Kilburn (1995) on Malaysia; Hertz (2001) on South Africa; Dunn (2007) and Ferreira and Veloso (2006) on Brazil; and Grawe (2001, 2004) on Ecuador, Nepal, Pakistan, and Peru. All the studies faced various data constraints but in general it is felt that intergenerational income mobility is lower in developing economies (Solon, 2002; Grawe, 2004). Malaysia remains the only Asian country studied.

This paper provides findings on a country in Asia which has undergone remarkable economic growth within a short span of time. In merely four decades since its independence in 1965, Singapore has transformed from a backward society rife with poverty and crime into a modern city with one of the highest per capita incomes (US$21,206 in 2002[1]) in the world. Educational policies accelerated the building of schools in the 1970s, making primary and secondary education in effect free and universal. These policies were instrumental in providing the younger generations with the qualifications for higher-skilled jobs that rapidly industrializing Singapore required (Mukhopadhaya, 2000).

We may expect that intergenerational mobility should be high in such a setting and that education has helped to improve mobility. However, the findings from the few studies on education and occupation in Singapore reveal that the conclusion is less clear. Chiew (1991) observed a generational upgrade in education, a phenomenon which is typical of the development process of industrialization. However, he also found high intergenerational correlation in education. That is, while those in the younger generation were more educated than their parents' generations, their educational attainment relative to their peers' persisted. Those whose parents were less educated were more likely to be less educated relative to their peers, while those whose parents were more educated were more likely to remain the most highly educated of their peers. Using the same data set as this paper, Ng and Ho (2006) also found a significant positive effect of parental education on youth's education.

Chiew (1991)'s transition matrices with four and ten occupational classes found both upward and downward occupational mobility across generations. For example, in the comparison of male respondents' to fathers' occupations (four categories), he found that 22.8% showed upward while 21% showed downward mobility relative to their fathers, amounting to a total mobility of 43.8%. Ong and

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Ho (2006)'s regressions of occupational prestige scores also concurs that Singapore's occupational mobility is high.

To my knowledge, there has been no study on intergenerational income mobility in Singapore. This paper aims to answer the question: how does intergenerational income mobility in Singapore compare with mobility in other countries? Given that education has played a vital role in economic advancement, the paper also analyzes: how has education promoted income mobility or persistence?

These questions are important to the development of Singapore and other countries which are facing similar economic and social realities. Due to globalization and skill-biased technological development, income inequality in Singapore has been widening. The inequality has widened not only in relative terms, but also in absolute terms (Singapore Department of Statistics, 2002).

In such a context of rising inequality, understanding intergenerational transmission of income becomes doubly important. By itself, intergenerational income mobility is an issue of concern because it is socially unjust that the poor remains poor and the rich continues to be rich. Additionally, when cross-sectional inequality is large and widening, low intergenerational mobility will perpetuate the widening inequality through generations.

Theoretically and empirically, mobility and equality do tend to move together. Solon (2004)'s theoretical model shows that both intergenerational elasticity and cross-sectional income inequality are "greater in the presence of stronger heritability, more productive human capital investment, higher returns to human capital, and less progressive public investment in human capital." Table 1 summarizes Gini indices and intergenerational elasticity coefficients (β) for various countries. For both, higher numbers indicate worse inequality or immobility.

Although cross-country comparisons can be problematic, the table shows that low mobility is associated with high inequality. The European countries tend to be more mobile and more equal than other countries. The exception is the U.K., where β is substantially higher. The U.S. is also relatively unequal and immobile compared to other industrialized countries. A recent study which uses a consistent approach to compare mobility in Britain, the U.S., West Germany, Canada, Sweden, Norway, Finland, and Denmark, concludes that "America and Britain have the highest intergenerational persistence (lowest mobility)" (Blanden, Gregg, & Machin, 2005).

The most unequal and immobile economies, however, may be developing countries such as Brazil and South Africa. Solon (2002) noted that mobility may be lower in developing countries, but that the dearth of studies on less developed countries does not allow us to "corroborate that conjecture".

Table 1: Inequality and Intergenerational Earnings Transmission Around the World

Country	Gini index*	β *(s.e.)*	Son's mean age	Father's mean age	No. of years of father's earnings	Estimation method	Author	U.S. equivalent
Developed countries								
Canada	31.5 (1994)	0.21 (N.A.)	32-35	45.5	5	LS	Corak (2006)	
		0.15 (0.004)	32-35	45.5	5	LS	Grawe (2004)	0.38 (0.09)
Denmark	24.7 (1992)	0.071 (N.A.)	40	35-64	1	LS	Jäntti et al. (2006)	
		-0.05 (0.094)	20.5	N.A.^	5	LS	Comi (2003)	
France	32.7 (1995)	0.41 (0.06)	30-40	55-70	-	IV	LeFranc and Trannoy (2005)	
		0.17 (0.042)	21.8	N.A.^	5	LS	Comi (2003)	
Germany	30 (1994)	0.11 (0.063)	22.8	51^	6	LS	Couch & Dunn (1997)	0.13 (0.061)
		0.095 (0.10)	≥25	31-56	5	LS	Grawe (2004)	0.14 (0.08)
		0.15 (0.05)	22.7	N.A.^	5	LS	Comi (2003)	
Sweden	25 (1992)	0.28 (0.09)	34.44	43.3	-	IV	Björklund and Jäntti (1997)	0.52 (0.138)
United Kingdom	36.8 (1995)	0.58 (0.06)	33	47.5	-	IV	Dearden et al. (1997)	
		0.58 (0.07)	33	≤57	1	Simulated LS	Grawe (2001, 04)	0.55 (0.17)
		0.09 (0.045)	20.5	N.A.^	5	LS	Comi (2003)	
United States	40.8 (1997)	0.47 (0.06)	28-41	40.2	3-5	LS	Grawe (2001, 04)	
		0.18 (0.03)	24-39	52^	8	LS	Altonji & Dunn (1991)	
		0.22 (0.04)	24-39	52^	-	IV	Altonji & Dunn (1991)	

Less-developed countries								
Brazil	60.7 (1998)	0.69 (0.01)	25-34	30-50	-	TSIV	Dunn (2007)	
Ecuador	43.7 (1995)	1.13 (0.29)	24-40	45-60	-	TSIV	Grawe (2001, 04)	
Malaysia	49.7 (1997)	0.27 (N.A.)	25	43/44	3	LS	Lillard & Kilburn (1995)	
		0.54 (0.22)	≥23	24-59	-	IV	Grawe (2004)	0.35 (0.10)
Nepal	36.7 (1995/ 1996)	0.32 (0.20)	24-40	45-60	-	TSIV	Grawe (2001, 04)	
Pakistan	31.2 (1996/ 1997)	0.24 (0.30)	25-35	45-60	-	TSIV	Grawe (2001, 04)	
Peru	46.2 (1996)	0.67 (0.17)	24-40	45-60	-	TSIV	Grawe (2001, 04)	
South Africa	59.3 (1993/ 1994)	0.609 (0.092)	25.1	53.7	1	LS	Hertz (2001)	

(Standard errors in parenthesis, where available)
*Source: World Development Report (2003)
^ contemporaneous

The next section surveys the literature on intergenerational earnings mobility. This is followed by a description of the Singapore National Youth Survey data, the challenges it poses for analysis and the econometric methods employed in estimating the intergenerational transmission of income. Interval regressions address the problem of grouped dependent variables. Incomes observed from the data include both transitory and permanent components, but only permanent incomes should matter to intergenerational transmission. To account for this, and for respondent errors, instrumental variables are used to predict permanent incomes. Estimates are then scaled to make results comparable with other studies. Section 4 reports the regression results. Effects of youth's education and disparity in mobility by ethnicity, sex and income are considered. The paper concludes with a summary and discussion of the implications for future economic inequality and public policy.

2. LITERATURE SURVEY

2.1 Baseline Empirical Model

The baseline empirical model used in measuring intergenerational earnings mobility is regression to mean through the following equation system:

$$\begin{aligned} & y_i^{child} - \bar{y}^{child} = \beta(y_i^{parent} - \bar{y}^{parent}) + \varepsilon_i^{child} \\ => \quad & y_i^{child} = (\bar{y}^{child} - \beta\bar{y}^{parent}) + \beta y_i^{parent} + \varepsilon_i^{child} \\ => \quad & y_i^{child} = \alpha + \beta y_i^{parent} + \varepsilon_i^{child} \end{aligned} \qquad (1)$$

where y_i is the logarithmic earnings of the individual, and $\bar{y}$ is the mean log of earnings of the individual's generation. The parameter β is hence the intergenerational earnings elasticity, or if the variances of log earnings in the two generations are similar, the intergenerational earnings correlation. A high β indicates low mobility.

However, elasticity estimates reported by different studies and on different economies are not comparable for several reasons. The data set in this paper faces all these comparability challenges, which I now outline in turn.

2.2 Transitory and Permanent Income

Some studies – such as Dearden et al. (1997) on England, Björklund and Jäntti (1997) on Sweden, and Hertz (2001) on South Africa - have only one year of earnings data. Estimates from using the observed one-year earnings are biased downward. This is because a given year's income comprises both transitory as well as permanent components, but only permanent earnings should be used to correlate earnings between the generations. To illustrate, the relation between observed and permanent parents' earnings is:

$$y_{it}^{parent} = y_i^{parent} + v_{it}^{parent} \qquad (2)$$

where y_i^{parent} is the permanent component, and v_{it}^{parent} is transitory "noise" that does not matter to permanent status.

When y_{it}^{parent} is used instead of y_i^{parent}, the resulting estimated β is less than the actual (unobserved) value:

$$p\lim \hat{\beta}_{direct} = \beta_{direct} = \beta\left[\frac{\sigma_y^2}{\sigma_y^2 + \sigma_v^2}\right] < \beta\,. \tag{3}$$

where σ_y^2 is the variance of permanent earnings and σ_v^2 is the variance of transitory earnings.

If data from multiple years is available, averaging over several years has helped to achieve better measures of permanent income and larger β estimates (e.g. Solon, 1992; Mazumder, 2005).

2.3 Instrumental Variables (IV)

Alternatively, researchers have instrumented for permanent earnings with measures of parents' status that is correlated with their earnings but not with v_{it}^{parent}. If we believe that y_i^{parent} is a function of some observed time-invariant factors (Q_i^{parent}) and time-invariant disturbance (f_i^{parent}), then (2) can be written as:

$$y_{it}^{parent} = y_i^{parent} + v_{it}^{parent} = \delta Q_i^{parent} + f_i^{parent} + v_{it}^{parent} \tag{4}$$

By running (4) as a first stage regression of y_{it}^{parent} on Q_i^{parent}, a predicted permanent earnings can be obtained:

$$\hat{y}_{Qi}^{parent} = \hat{\delta} Q_i^{parent} \approx y_{it}^{parent} - f_i^{parent} - v_{it}^{parent} \tag{5}$$

This predicted value is then used in the intergenerational equation (1), as follows:

$$y_i^{child} = \alpha + \beta \hat{y}_{Qi}^{parent} + \mu_i^{child} \tag{1'}$$

The resulting intergenerational transmission estimate, $\hat{\beta}_{IV}$, will be biased upwards if the instruments are themselves direct factors in the equation of children's economic achievement in (1). In the literature, parents' education (e.g. Solon, 1992) and occupational status (e.g. Zimmerman, 1992) have been used as instruments, but parents' education is said to have a direct effect on their children's economic outcomes. Current estimates by IV have been larger than direct estimates (e.g. see results for Altonji & Dunn, 1991; Dearden et al. 1997; Grawe, 2004; and Dunn, 2007 in Table 1).

2.4 Lifecycle variation

There are two parts to the biases caused by measuring incomes at different life stages. One pertains to the age of offspring and the other to the age of parents. Haider and Solon (2006) show that instead of an errors-in-variable relationship between current and lifetime earnings as in equation (2), life cycle variation in earnings results in a more general relationship:

$$y_{it}^{parent} = \lambda_p y_i^{parent} + v_{it}^{parent}, \tag{6}$$

Applying this into the intergenerational equation (1) gives a bias that could theoretically be an attenuation or an amplification, as follows:

$$p\lim \hat{\beta}_{direct} = \beta\left[\frac{\lambda_p \sigma_y^2}{\lambda_p{}^2 \sigma_y^2 + \sigma_v^2}\right]. \tag{7}$$

Haider and Solon's (2006) empirical estimations, however, continue to get attenuation biases. They find that "$\hat{\lambda}$ begins at 0.24 at age 19, increases steadily until it rises to about 1 at age 32, and then declines some in the late forties". This gives an attenuation bias that "begins at only about 0.2, increases to a fairly flat peak averaging about 0.65 between the late twenties and mid forties, and then decreases".

Two further implications of this non-classical error are that using instrumental variables (IV) and current income for the dependent variable will no longer be consistent. IV estimators will now equal β / λ_p instead of β. The coefficient from using current income for youth will be $\lambda_y \beta$, where λ_y is the coefficient in the linear projection of the log of the youth's current income on the log of their lifetime income.

For samples of young offspring, λ_y is likely less than λ_p and all my estimates should be under-estimated. Reville (1995) shows this to be so in the U.S. His β estimate equals 0.25 when sons are in their 20s, and 0.5 when sons are in their 30s. Investigations in other countries which have younger samples - such as Lillard & Kilburn (1995) on Malaysia, and Corak & Heisz (1999) on Canada – also tend to have lower estimates.

For the age of parents, Corak (2006)'s review of a few American studies summarizes that "the average estimate is 0.154 when fathers are on average 50 years or older, 0.406 when they are between 45 and 49 years, and 0.433 when they are younger than 45 on average".

Putting young age of offspring and mature age of parents together, when studies have contemporaneous data from parents and offspring, elasticity estimates will be doubly reduced. Indeed, studies which used contemporaneous data turned in low estimates. Couch and Dunn (1997), for example, replicated Germany's sampling in the U.S., and obtained a β of 0.11 and 0.13 respectively. The latter estimate for the U.S. is smaller than the other U.S. magnitudes in Table 1. Comi (2003) used a common cross-section data set for several countries in Europe. All her estimates are very small. Two countries – Denmark and the Netherlands – even had negative βs (see Table 1).

2.5 Categorical Income

In Dearden et al. (1997), father's earnings were in ranked categories. They dealt with this in two ways. One was to continue with the usual ordinary least squares (OLS) using midpoints of categories. Another was to use Stewart's (1983) Grouped Dependent Variable (GDV) estimator. This method is now a command in STATA as "interval regression". A generalization of the tobit regression, the interval regression model starts as usual with:

$$y_i = X_i\beta + \varepsilon_i$$

where y_i is the unobserved continuous outcome and $\varepsilon \sim N(0, \sigma^2 I)$.

Interval regression then maximizes the following log likelihood function through iterations of moment estimations:

$$\begin{aligned} \ln L = & \sum_{i \in L} \log \Phi\left(\frac{y_{Li} - X_i\beta}{\sigma}\right) \\ & + \sum_{i \in R} \log\left\{1 - \Phi\left(\frac{y_{Ri} - X_i\beta}{\sigma}\right)\right\} \\ & + \sum_{i \in I} \log\left\{\Phi\left(\frac{y_{2i} - X_i\beta}{\sigma}\right) - \Phi\left(\frac{y_{1j} - X_i\beta}{\sigma}\right)\right\}. \end{aligned} \tag{8}$$

$i \in L$ are left-censored. That is, we know only that y_j is less than or equal to y_{Li}.
$i \in R$ are right-censored. We know only that y_j is greater than or equal to y_{Ri}.
$i \in I$ are intervals. We know only that y_j is in the interval $[y_{1j}, y_{2j}]$.
$\Phi(.)$ is the standard cumulative normal.[2]

[2] Source: STATA Release 9 Reference A-J.

If one needs to conduct instrumental variables estimation on ranked interval data, a two-stage interval regression system can be modeled as follows. First, the equations in the first and second stages are:

$$y_i^{parent} = Z_i^{parent}\gamma + \upsilon_i \tag{9}$$
$$y_i^{child} = \alpha + \beta y_i^{parent} + X_i^{child}\delta + \varepsilon_i \tag{10}$$

where y_i^{child} and y_i^{parent} are unobserved continuous variables and $(\varepsilon_i, \upsilon_i)$ are assumed to be bivariate normal with mean zero. Thus, we can write:

$$\varepsilon_i = \upsilon_i'\Pi + \mu_i, \tag{11}$$

where $\Pi = \frac{\sigma_{\varepsilon\upsilon}}{\sigma_\upsilon^2}$.

The log likelihood function can then be written as:

$$\ln L = \ln f(y_i^{child} \mid y_i^{parent}, Z_i^{parent}, X_i^{child}) + \ln f(y_i^{parent} \mid Z_i^{parent}) \tag{12}$$

where:

$$\begin{aligned}\ln f(y_i^{child} \mid y_i^{parent}, Z_i^{parent}, X_i^{child}) = &\sum_{i\in L}\log\Phi\left(\frac{y_{Li}^{child} - m_i}{\sigma_{\varepsilon|\upsilon}}\right)\\ &+\sum_{i\in R}\log\left\{1-\Phi\left(\frac{y_{Ri}^{child} - m_i}{\sigma_{\varepsilon|\upsilon}}\right)\right\}\\ &+\sum_{i\in I}\log\left\{\Phi\left(\frac{y_{2i}^{child} - m_i}{\sigma_{\varepsilon|\upsilon}}\right)-\Phi\left(\frac{y_{1i}^{child} - m_i}{\sigma_{\varepsilon|\upsilon}}\right)\right\},\end{aligned} \tag{13}$$

$$m_i = \alpha + \beta y_i^{parent} + X_i^{child}\delta + \Pi(y_i^{parent} - Z_i^{parent}\gamma), \tag{14}$$

and

$$\begin{aligned}\ln f(Y_i^{parent} \mid Z_i^{parent}) = &\sum_{i\in L}\log\Phi\left(\frac{y_{Li}^{parent} - Z\gamma}{\sigma_\upsilon}\right)\\ &+\sum_{i\in R}\log\left\{1-\Phi\left(\frac{y_{Ri}^{parent} - Z\gamma}{\sigma_\upsilon}\right)\right\}\\ &+\sum_{i\in I}\log\left\{\Phi\left(\frac{y_{2i}^{parent} - Z\gamma}{\sigma_\upsilon}\right)-\Phi\left(\frac{y_{1i}^{parent} - Z\gamma}{\sigma_\upsilon}\right)\right\}.\end{aligned} \tag{15}$$

Practically, the procedure is similar to a two-stage least squares. The first stage is an interval regression of parental income on father's education, father's occupation and the control variables. The second stage is an interval regression of youth income on the predicted parental income from the first stage and control variables.

2.6 Father's Earnings or Parents' Income

Corak (2004) suggests that as a measure of family resources, β values from father's earnings will be underestimated compared to parental or family income. Indeed, studies which compared effects of parental income and earnings found larger estimates from parental income. In Behrman and Taubman (1990), elasticity of contemporaneous data in the U.S. is 0.13 for earnings compared to 0.27 for income. Eide and Showalter (1999) used five years of father's earnings versus family income. Their estimates were 0.34 and 0.45 respectively. For these two studies, then, parental or family income yielded estimates that are between 1.3 to 2.1 times (for an average of 1.7 times) that of earnings.

2.7 Cross-country Comparability

In recent years, researchers have attempted to make elasticity estimates more comparable across countries by replicating on U.S. data the sample selections and statistical methods in studies of other countries.

Table 1 summarizes the key features and findings in a sample of mobility studies. It reflects the statistical biases discussed above, where estimates tend to be larger at middle age ranges of children and parents, when more years of father's earnings/income are used, and with IV estimation. Besides listing countries by estimation methods, I also included a "U.S. equivalent" from the estimates of studies which replicated the sampling and methods of that country on U.S. data. While some countries, such as Sweden and Canada, continue to show higher mobility than the U.S., countries such as Germany and Malaysia do not look as mobile anymore. Lillard and Kilburn (1995)'s estimate of 0.27 looks moderate until Grawe (2004) re-estimates it to be 0.54 by IV. This is larger than the U.S. equivalent of 0.35. Independently, Germany's estimates are small relative to U.S. estimates but Grawe (2004) and Couch and Dunn (1997)'s comparative estimates indicate otherwise.

2.8 Nonlinear Mobility

A single β estimate assumes uniform mobility throughout an economy. However, we may expect nonlinear persistence for two possible reasons. In the classic case originating from Becker and Tomes (1979, 1986), the relationship between parents' and children's earnings is concave, because credit constraints limit a poor family's ability to invest in human capital for children's future higher earnings. However, this reason has not found much empirical support. Grawe (2004)'s quantile regressions did find that compared to other countries in his study, U.S. and Canada had less earnings persistence in upper quantiles than in lower quantiles. However, he cautioned against firm conclusions due to inconsistent results from the two U.S. data sets he used. Other studies, such as Solon (1992) and Bratsberg et al. (2007), also did not find any nonlinearity in U.S. mobility. Using higher order polynomial terms, Bratsberg et al. (2007) instead found a convex pattern for Denmark, Finland and Norway. They attributed this to educational systems which promote opportunities for the poor, hence counteracting the effects of credit constraints. This then led to an overestimation of the difference in mobility between these countries and the U.S. and U.K., which had linear mobility patterns.

2.9 Mobility and Education

Based on the two types of nonlinearity, education is a double-edged sword. On one hand, it is a means through which parents invest in their children's future earnings. On the other hand, it is also a way to equalize opportunities for poor children.

Bowles (1972) demonstrated the heavy dependence of educational qualifications on parental socioeconomic background. In his regressions of respondents' earnings on parental social background variables, adding years of schooling as a covariate increased the variance by only 2.1%. Hence, "most of the impact of years of schooling on earnings appears to be a direct transmission of economic status from one generation to the next." Eide and Showalter (1999), on the other hand, found that the lower quantiles had the largest education coefficients. This suggests that education is more valuable to the lower income.

What then does returns to education measure? Does it measure the independent effects of education itself or simply socioeconomic background? The former would increase mobility whereas the latter would increase persistence. Other studies suggest that whether it is the former or latter depends on the education regimes, where systems which provide better access to education for poorer families yield more mobile societies. Solon's theoretical model (2004) finds that a more progressive public investment in human capital (i.e. less dollars spent on richer students) tends to increase mobility. Another theoretical model by Davies, Zhang & Zeng (2005) finds that "starting from the same inequality, mobility is higher under public than under private education." An empirical study of Britain by Blanden, Gregg & Machin (2005) finds that "the big expansion in university participation has tended to benefit children from affluent families more and thus reinforce immobility across generations".

What do these findings mean to a country such as Singapore? We may expect the universal expansion of education in the 1970s to have generated more independent returns to schooling and improved mobility. Perhaps the findings for Malaysia are applicable, since its economic situation, demographic profile, and socio-political institutions are similar to Singapore. Unfortunately, while Lillard & Kilburn (1995) showed that adding schooling greatly reduces the effects of father's earnings, they did not report how much more schooling explains variation in offspring's earnings.

3. DATA & METHODOLOGY

3.1 Survey data

The data source for this study is the National Youth Survey (NYS) conducted by the National Youth Council in 2002. This was a one time cross-sectional survey. Only youth were interviewed. The purpose of the survey was to understand the state of youth in Singapore and hence, the majority of the questions in the survey were about youth attitudes, family, and social relations.[3] However, variables needed for an analysis of intergenerational income mobility were included in the NYS, albeit in less sophisticated forms than most other data sets used in the literature.

Although a total of 1,504 youth aged 15-29 were surveyed, this study restricts the sample to youth aged 23 to 29 who were working full-time.[4] Cases where the reported occupation is "not classifiable" - the majority of whom are national servicemen - are also dropped. Although national service is considered full-time employment, its meager and standardized stipend does not reflect true earnings potential.

[3] Adding family support and challenge variables to my regressions did not change my estimates much, and the effects of these two groups of variables were weak or volatile. See also footnote 8.

[4] Table A.1 gives the breakdown of how the sample size decreases as I exclude different types of respondents. I distinguish full-time workers from part-time and non workers with NYS' question on occupation, which gives the following choices: (1) occupation category, (2) refused to answer, (3) none/unemployed, (4) homemaker, (5) student. This schema therefore identifies respondents according to his or her primary occupational status. Only respondents in group (1) are included in my sample because the monthly incomes reported for respondents in the other group, when available, are all in the lowest three income categories ($1,500 or less), indicating part-time work or work that may be less than their earning potential. The NYS does not ask about hours of work, except students' part-time hours during the school semester.

In the main analysis, I also drop cases where fathers were retired, unemployed or refused to answer. Table A.2 in the Appendix shows that retired fathers have substantially lower income levels than the overall sample. This may be because reported incomes are from lower post-retirement salaries or from the last jobs held many years ago and when the earnings profiles have tapered off. Hence, including incomes from fathers who are not working will likely bias results. Besides cases I dropped, parents' income is missing for 88 cases. This leaves me with a maximum sample size of 271 with valid values of both youth and parents' income.

Due to the high attrition of sample size, I also report alternative results from a multiple imputation of missing and retired parents' incomes[5], missing father's occupations, missing father's education, and missing youth income. First, multiple data sets with imputed values are created. This is done using the ICE command in STATA, which imputes missing values "by using switching regression, an iterative multivariable regression technique" (Royston, 2004). Regression estimates are then derived for each data set and pooled.

Multiple imputation requires the assumption that missing observations are missing at random (MAR) or missing completely at random (MCAR). Tables A.3a and b report the missing patterns. I used only income, education, and occupation as independent variables in the imputations because they did not vary significantly by other variables such as age, sex, and ethnicity.

3.2 Income

The NYS queries youth about income with the questions "what is your monthly income from all sources?" and "what are your parent's combined monthly income from all sources?" The answers to these questions are not reported in actual numeric values but in nine ranges: less than S$500; S$500-S$1,000; S$1,001-S$1,500; S$1,501-S$2,000; S$2,001-S$3,000; S$3,001-S$5,000; S$5,001-S$7,500; S$7,501-S$10,000; S$10,001 and above.

The nature of these questions and other limitations in the data set result in all the methodological challenges described in the previous section. First, because income is given in categories, I apply interval regression rather than the standard OLS. I had also used midpoints of ranges as values in an OLS[6].

[5] Analysis without imputation of retired father's incomes gives slightly smaller coefficients. This is consistent with the observation that reported incomes of parents where fathers are retired may not be their average lifetime income, but income when earnings have tapered off or from post-retirement job.

[6] For the two unbounded categories at the ends, I impute S$250 (half of the upper bound) for the lowest category and S$20,000 (twice the upper bound) for the highest category. The choices are somewhat arbitrary. Varying their values did not change results, because there were only 2 parents are in the lowest category and 17 parents in the highest category. I also tried estimating mean

However, I report only interval regression results as the estimates from the two approaches are almost identical.

Second, although the question specifies "from all sources", in a survey setting, respondents are likely to under-report non-labor income. Therefore, the results are likely to be between elasticity measures from true earnings and true income.

Third, with only one year of income, elasticity estimates are likely to be attenuated. Hence, I instrument for permanent income with education and occupation. I had tried different combinations of instruments. For example, using only father's occupation often decreases the size of estimates. This is consistent with the scenario observed in Chiew (1991) and Ong and Ho (2006) that intergenerational occupational mobility is high, and that "the occupational class structure is quite flexible" (Chiew, 1991) in Singapore. If occupational mobility is greater than income mobility, then using occupation to instrument for income would result in smaller estimates.

On the flip side, using only father's education gives very big estimates, and this, as Solon (1992) has argued, may be because father's education matters directly for a youth's own economic outcome. Therefore, I report results using both education and occupation, as the two together should give a closer approximation of income status (and more data points for the second stage regression).

Tables A.4 and A.5 report the correlation coefficients between the income variables and the instruments. They show the reasonable strength of the chosen instruments. The correlation coefficients also support the plausibility of the above explanations on occupation and education as instruments. The correlation between parental and youth occupations is much lower than that for income and education. Parental education has a stronger correlation with youth income than parental occupation.

The fourth challenge is that parents' incomes in the NYS are not self-reports, but reports by the children. This source of reporting error is not as problematic in this data set for two reasons. Firstly, predicting permanent measures of income using instrumental variables should reduce the margin of error from the lack of self-reports. Secondly, as Figures A.1 and A.2 illustrate, the NYS income distributions are reasonable compared with Census statistics, matching more closely with Census personal than household income. The distributions for education and occupational class are also similar to the distributions from Census 2000 (Figures A.3 to A.6), except that a higher percentage of NYS parents are primary educated or below, and a slightly higher

values by fitting a pareto distribution as done by Aigner and Heins (1967). However, the resulting slope coefficients did not meet the criterion of a value less than -2, not surprising given the small number of categories.

percentage of NYS parents are skilled rather than highly skilled. Overall, the distributions reflect the life stages of the youth and their parents, as well as the upgrade in educational and occupational status of the younger generation.

The final data problem is the issue of lifecycle variation in incomes. The NYS gives concurrent incomes of youth early in their careers and parents near retirement or in semi- or full retirement. While youth's incomes are still rising to their full potential, parents' earnings may be tapering off. Current studies adjust for life cycle variation by controlling for age. However, the NYS reports age of youth in categories and does not give parents' ages. I partially adjust for age of offspring by including in my regressions a dummy for being in the younger age group.

Not controlling for parents' age may not be as problematic in this data set. Figure A.7 plots the age-earnings profiles of nine occupational classes in Singapore. It shows that whereas the profiles do climb at younger ages, the profiles remain flat rather than turn downwards at older ages (except for agricultural workers). How old are the parents in NYS likely to be? According to the Singapore Report on Registration of Births and Deaths and Marriages, in 1973 and 1979 (the years of birth of the youngest and oldest youth in the sample), mode and median age ranges of marriage are 20 to 25 for females and 26 to 29 for males. Mode and median ages of mothers at birth of children are 25 to 29. This translates to a rough parental age range of between 45 and 54 in 2002 (all age information available in published reports is in ranges/categories). Hence, with an official retirement age of 62, the majority of parents in the age range are still in full-time employment.

Two other factors reduce error from late-in-life reporting of parental income. One, since the NYS asked for current income, error due to retrospective reporting is absent. This serves as a counteracting force to the response error of youth reporting their parents' incomes. Two, the econometric methods that will be used to get permanent measures should also help to obtain predicted values of parental income more aligned to their class status.

3.3 Instrumental and Control Variables

The NYS reports education in categories, some of which overlap in terms of the educational level. This is due to different tracks that students may pursue. Table A.6 shows the transformation from the NYS categories to a scale indicating a total of six levels of education: 1 "none", 2 "primary & below", 3 "secondary", 4 post-secondary, 5 "bachelor degree", and 6 "graduate degree". Although the transformed classification is somewhat arbitrary, it may be a best estimate of the overlapping levels of qualifications which an alternative measure such as years of schooling will inaccurately reflect.

For occupation, I converted the Singapore Standard Occupation Classification used in the NYS data set to the Singapore Occupational Prestige Score (SOPS) from Chiew et al. (1991). SOPS was developed by replicating the U.S.-based National Opinion Research Center (NORC) survey in Singapore, and includes local occupations such as "Buddhist monk, Chinese physician, coffee shop proprietor, Hindu priest, Imam, and smuggler". Table A.7 in the Appendix shows the SOPS scale corresponding to the occupational group in the NYS.[7]

Age and ethnicity are dichotomous variables. The age dummy equals one if respondents are aged 23 to 25. Ethnicity equals one for non-Chinese respondents.

3.4 Empirical Approach

I start with a direct interval regression that takes log of youth's incomes on the mid-point of log of parent's income categories. I control for age and sex dummies. Then I apply IV estimation by two stage interval regression. The second stage uses predicted parent's income from a first stage interval regression of log of parent's income on education, occupation, youth's age and sex. Next, I add youth's education to both the direct and IV regressions to study the attenuation effect of education on intergenerational income elasticity. Then I test for differences in mobility by sex and ethnicity by adding interaction terms in the direct regressions.[8] Finally, I test for nonlinearity in mobility through quadratic parental income.

I repeat all the above on the imputed data. The imputations increase the sample size to 539. Overall, I expect the direct regression from the imputed sample to be a lower bound because imputing tends to compress variability. I expect IV regression from the imputed sample to be an upper bound because the same variables are used in imputation and as instruments.

After estimation, I perform two transformations. First, I apply my computed scale factor from Behrman and Taubman (1990) and Eide and Showalter (1999) to translate from income to earnings elasticity. This gives very conservative estimates because I believe that some respondents gave earnings

[7] Besides SOPS, Chiew et al. (1991) report two other scales: (1) the Singapore NORC (SNORC), a direct application of NORC on Singapore occupations; and (2) the Abbreviated Occupational Scale (AOS), which has only nine categories, and "follows the categories used in Duncan's Socioeconomic Index and the U.S. Census Socioeconomic Status Classification". I have chosen to report the SOPS for the intuition that it most closely reflects prestige valuation in the Singapore context. The three scales are very similar and regressions using the SNORC and SOPS give almost identical results.

[8] I also tested other possible mediating variables, namely family challenge and support, whether single or married, and whether living with parents. In most cases, including these variables changed the estimate sizes of the main explanatory variable - parental income - minimally.

rather than incomes. Second, I use Corak (2006)'s scaling of Couch and Dunn (1997) to estimate elasticities should offspring be older and parents be younger. Among the studies in Table 1 with a U.S. equivalent, the age of offspring and parents in my sample are closest to those in Couch and Dunn (1997). Although my estimates use IVs whereas theirs take average earnings over six years, the two methods may even out. While these scales do make results more comparable, they are of course limited. They depend on strong assumptions such as similar income distributional structures in different countries.

4. RESULTS

Table A.8 provides the descriptive statistics of the key variables. The ethnic composition is comparable to that of the national youth sample and is predominantly Chinese. Females are however over-represented in the sample, largely because of the exclusion of males who are in National Service. The NYS also oversamples youth in the younger age group.

As noted before in the discussion of data challenges, the educational and occupational distributions of respondents and their parents (Figures A.3 and A.5) show that the economic outcomes of the later generation have improved relative to the previous generation. This is important for economic development. However, to what extent can people break free from inherited economic status of their families? Or do those whose parents have low economic status within their generation continue to have low economic status compared to their peers, even though their economic levels have improved relative to their parents? Do kids of rich parents continue to be the richest in their generation?

Table 2 presents the estimates of β under different specifications. The top panel gives the results with casewise deletion. Direct interval regression yields an estimated elasticity of 0.23. When education is added, the effects of parental income are attenuated by 35%. Therefore, a substantial portion of parents' transmission of their income advantage is through their investments in their children's education. However, education does exert some, although small, independent returns. The log-likelihood values show that education explains an additional 8.8% of the variation in youth's income. This is four times more than the 2.1% which Bowles (1972) found.

Compared to the direct regression results, β by instrumental variables is larger at 0.28 without respondents' education, but attenuated more (57%) when youth's education is included. This is unsurprising since parental education has direct effects on youth income as well as education. Adding education improves the log-likelihood by 8.5%, not much lower than the direct regression case.

Table 2: Interval Regression Estimates of Intergenerational Income Elasticity

Sample with Casewise Deletion						
	Direct		IV^		Interactions	Quadratic
	No edu	+ Edu	No edu	+ Edu		
Log(parents' income)	0.23 (0.028)**	0.15 (0.027)**	0.28 (0.049)**	0.12 (0.044)**	0.21 (0.043)**	0.14 (0.37)
Log(parents' income)^2						0.006 (0.023)
Respondent's education		0.22 (0.026)**		0.23 (0.029)**		
Age 23-25	-0.17 (0.046)**	-0.14 (0.042)**	-0.18 (0.048)**	-0.14 (0.045)**	-0.20 (0.046)**	-0.17 (0.046)**
Female	-0.033 (0.046)	-0.056 (0.041)	-0.041 (0.048)	-0.055 (0.041)	-0.046 (0.049)	-0.032 (0.046)
(Female) x Log(parents' income)					0.016 (0.055)	
Non-chinese					-0.19 (0.059)**	
(Nonchinese) x Log(parents' income)					0.057 (0.069)	
Constant	5.91 (0.22)**	5.72 (0.20)**	5.59 (0.37)**	5.89 (0.29)**	7.72 (0.048)**	6.29 (1.50)**
Observations	271	271	271	271	271	271
Log likelihood	-378.30	-346.86	-390.05	-357.68	-373.31	-378.27

Sample with Imputation^^						
	Direct		IV^		Interactions	Quadratic
	No edu	+ Edu	No edu	+ Edu		
Log(parents' income)	0.17 (0.022)**	0.088 (0.020)**	0.26 (0.031)**	0.10 (0.034)**	0.13 (0.031)**	0.28 (0.29)
Log(parents' income)^2						-0.006 (0.018)
Respondent's education		0.23 (0.018)**		0.23 (0.023)**		
Age 23-25	-0.16 (0.035)**	-0.15 (0.031)**	-0.16 (0.036)**	-0.15 (0.032)**	-0.18 (0.035)**	-0.16 (0.036)**
Female	-0.056 (0.035)	-0.073 (0.031)*	-0.063 (0.035)	-0.075 (0.030)*	-0.078 (0.038)*	-0.062 (0.035)
(Female) x Log(parents' income)					0.059 (0.043)	
Non-chinese					-0.19 (0.048)***	
(Non-chinese) x Log(parents' income)					0.051 (0.056)	
Constant	6.41 (0.17)**	6.16 (0.15)**	5.72 (0.24)**	6.04 (0.24)**	7.75 (0.034)**	5.96 (1.19)**
Observations	539	539	539	539	539	539
Log likelihood	-797.85	-729.18	-792.94	-729.44	-788.47	-797.71

(Standard errors in parentheses) * significant at 5%; ** significant at 1%

^ Standard errors are estimated by bootstrap sampling, ^^ Within-imputation standard errors are reported

While the coefficients of youth's education are themselves sizeable and significant, we have to bear in mind the endogeneity of this variable. An unobserved variable such as ability may have influenced both education and income.

Including interaction terms attenuates β slightly. However, the results indicate that intergenerational elasticity does not differ by race or sex, although non-Chinese respondents do have significantly lower incomes than Chinese. Finally, the quadratic specification indicates no nonlinearity. Figure A.8 gives the scatter plot of youth income against parent's income with a linearly fitted line on the left and a quadratic fit on the right. Both graphs show that the relationship between youth and parents' income is more linear than curvilinear.

The bottom half of Table 2 reports estimates with imputation. To achieve for all coefficients rates of missing information that are less than 62% and efficiency rates of at least 90%, estimates were derived from ten data sets for the quadratic specification and from five data sets for the other specifications.

The results from the imputed sample are similar to those from the original sample, with two exceptions. First, consistent with the expectation of smaller estimates due to variability compression, the magnitudes of estimates with imputation are smaller than when cases are dropped. Only the quadratic specification in the last column gave a higher elasticity in the imputed sample. Second, while youth income does not differ by sex in the first sample, it does in some specifications of the imputed sample.

To compare against estimates from other countries, let us use the direct (0.23) and IV (0.28) estimates from the sample with deleted cases, as the lower and upper limits respectively. Imputation may have over-condensed the estimate because of both compressed variability and single-year predictors.

Let us now transform this 0.23 to 0.28 range into something comparable to other studies. First, if the reported incomes are indeed incomes and not earnings, and if the relationship between income and earnings is similar in America and Singapore, I can divide my estimates by 1.7, the average scale factor computed from Behrman and Taubman (1990) and Eide and Showalter (1999). The range now gives a conservative earnings elasticity of between 0.135 and 0.16.

Since some respondents may have reported their earnings rather than income, the true estimate should be more than 0.135 (as a lower limit) and less than 0.28 (as an upper limit). This is a very wide range that makes it difficult to precisely locate where Singapore's level of mobility is compared to other countries. However, I think the range shows clearly that mobility in Singapore is definitely not high, but may instead be on the low end. Comparing straight with Couch and Dunn (1997) and Comi (2003), which had similar age profiles of youth and parents, Singapore's estimates look within range or higher than those for Germany, France, U.S., and Britain (see Table 1).

Corak (2006) used Grawe (2004)'s 0.47 for the U.S. as the benchmark to scale other estimates to something which reflects the elasticity for a 45 year old with average father's earnings from 5 to 15 years. If we apply the same scale factor Corak used on Couch and Dunn (1997), Singapore's scaled estimate should be multiplied by 4.3 (0.47/0.11). This gives a β range of 0.58 to 1.20. These numbers are very high compared to those from Canada and Scandinavian countries, which the literature has found to have the lowest β values.

Comparison between Singapore and less developed countries is less straightforward because the age profiles in studies on these countries neither fit my original nor transformed profiles. However, it is probably not far-fetched to conclude that the mobility situation in Singapore is mid-range among the developing countries. For example, the age profile of my sample is similar to Grawe (2004) for Ecuador, Nepal, Pakistan, and Peru, except that Grawe's youth extend to 40 years of age. If I take the lower bound of the scaled range, 0.58, to compare with Grawe's results, Singapore is worse than Nepal and Pakistan but better off than very immobile countries such as Ecuador.

5. IMPLICATIONS FOR DEVELOPMENT, INEQUALITY, AND POLICY

My analysis using direct regressions and instrumental variables to predict permanent income give an intergenerational income elasticity which ranges from 0.23 to 0.28. This translates to an earnings elasticity within the range 0.135 to 0.28 and 0.58 to 1.20 if the respondents are aged about 45 years old. Although these transformations provide only limited inter-country comparability, I believe it is fair to conclude that mobility in Singapore is moderately low when compared internationally. There seems to be no ethnic or sex disparity in intergenerational income mobility, nor does there seem to be differing mobility by income class. However, while universal education upgraded the educational qualifications of a whole generation, it may not have been as effective as an agent of intergenerational mobility. Most of the returns from schooling seem to derive from parents' economic status.

These findings show no looming disparity problem in Singapore. However, taken in context of Singapore's stage of economic development and state of social policy, the findings portend greater and greater inequality problems that policy makers should not ignore.

Now that the economy is maturing, and the population has become educated and skilled, Singapore can no longer rely on double-digit economic growth and widespread educational upgrade to enrich large portions of the population as in the past. Without the leverage of another large increment in education, can education policy help level the playing field? Current educational trends seem to suggest that the answer is no. From a more universal public education system, primary and secondary education is now becoming more privately run. With the advent of independent and autonomous schools, for example, there is more stratification in the quality of schools, with higher quality schools being more expensive. In light of the theoretical literature showing lower mobility in private and regressive educational regimes, and the evidence from Britain where the expansion of tertiary education benefited affluent families more, will there be a decrease in mobility, and a widening gap in relative mobility of different income groups? As the economy becomes increasingly knowledge-based, will those lacking the requisite skills be left farther and farther behind? The recent drop in earnings of the bottom wage earners show that this may already have started.

Economic and social policy in Singapore has intentionally upheld the value of individual improvement through contribution to the economy, with good reasons and so far with very successful outcomes. She has shied away from the welfare state models of the West, choosing instead a social security system based on individual savings accounts. She has adopted a manpower policy with no unemployment insurance, but instead an emphasis on retraining. All these are meant to encourage productive contribution to the economy because this small nation with no natural resources relies heavily on its industrious work force for individual and national economic progress. These systems, however, are innately regressive. At this stage of Singapore's economic and social development, there has been rising concern in public debate over the need for a stronger social safety net.

In view of the rising trend of moderate inequality, how should the government balance the priorities of economic development and equity? With the changed world that the younger generation faces, should resources continue to be devoted to improving the value-added of the most productive workers (e.g. through an educational system that rewards the brightest), or should greater priority be given to ensuring a stronger safety net for those who fall behind?

APPENDIX

Table A.1: Reduction in Sample Size as Cases are Dropped

Age 23-29	673
- refused to answer occupation	2
- unemployed	27
- homemaker	23
- student	22
- occupation not classifiable	35
Subtotal	564
- refused to answer father's occupation	52
- father unemployed	22
- father retired	130
- father's occupation not classifiable	1
- parents' income missing	88
Total N	271

Note: Sample includes only youth who reported positive income and valid educational qualification.

Table A.2: Summary Statistics of Income, Occupation and Education by Subsamples

	N	Mean	Median	SD	Min	Max
All (Age 23-29)						
Parents' income (Mid-point of categories)	413	3,222.16	1750	4,344.94	250	20,000
Father's SOPS scale	480	41.28	26	21.61	11	68
Father's educational level	513	2.80	3	1.15	1	6
Youth's SOPS scale	592	50.49	63	18.35	11	68
Youth's education	591	3.95	4	0.92	2	6
Parents with missing income						
Father's SOPS scale	130	44.87	46	21.90	11	68
Father's education	138	2.84	3	1.27	1	6
Retired fathers						
Parents' income (Mid-point of categories)	71	1,757.04	750	3,459.71	250	20,000
Father's SOPS scale	117	44.54	29	21.76	11	68
Father's education	123	2.84	3	1.21	1	6
Fathers with SOPS missing						
Parents' income (Mid-point of categories)	63	2,742.06	1250	4,398.95	250	20,000
Father's education	59	2.76	3	1.18	1	6

Table A.3a: Patterns of Missing Values of Parents' Economic Status

	Parents' Income	Father's SOPS	Father's Education	N
1	√	√	√	275
2	*	√	√	179
3	*	*	√	59
4	*	*	*	52
5	*	√	*	22
6	√	√	*	4
7	√	*	*	1

√ denotes value present, * denotes missing value

Table A.3b: Patterns of Missing Values of Youth's Economic Status

	Youthinc	educ	N
1	√	√	567
2	*	√	24
3	√	*	1

√ denotes value present, * denotes missing value
No youth occupational class missing because all youth with unclassifiable occupational status are dropped.

Table A.4: Correlation Coefficients of Income Variables and Their Instruments

	Youth Income	Parent Income	Youth Education	Youth Occupation (SOPS)	Father's Education	Father's Occupation (SOPS)
Income	1.0					
Parent's income	0.34	1.0				
Youth education	0.39	0.34	1.0			
Youth occupation (SOPS)	0.32	0.19	0.48	1.0		
Father's education	0.27	0.58	0.42	0.16	1.0	
Father's occupation (SOPS)	0.24	0.49	0.37	0.10	0.57	1.0

Table A.5: Correlation Coefficients of Income Variables and Their Instruments with Imputations

	Youth Income	Parent Income	Youth Education	Youth Occupation (SOPS)	Father's Education	Father's Occupation (SOPS)
Income	1.0					
Parent's income	0.31	1.0				
Youth education	0.53	0.34	1.0			
Youth occupation (SOPS)	0.47	0.19	0.48	1.0		
Father's education	0.31	0.66	0.39	0.21	1.0	
Father's occupation (SOPS)	0.22	0.61	0.31	0.14	0.52	1.0

Table A.6: Educational Levels in Singapore

Level	As used in paper	Youth in survey	Father in survey
1	None	None	None
2	PSLE and below	PSLE and below	PSLE and below
3	Secondary/ITE	GCE `N'	GCE `N'
		GCE `O'	GCE `O'
		ITE/Vocation Institute	ITE/Vocation Institute
4	Post-secondary /Polytechnic	GCE `A'/Post secondary	GCE `A'/Post secondary
		Polytechnic /professional certificate	Polytechnic /professional certificate
5	Bachelor	University degree	University degree
6	Graduate Degree	University postgraduate degree	University postgraduate degree

PSLE= Primary School Leaving Certificate
GCE=General Certificate of Education
ITE=Institute for Technical Educaiton

Table A.7: Occupational Classification and Prestige Scale in Singapore

SSOC	SOPS
Legislators, senior officials and managers	68
Professionals	64
Associate Professionals and technicians	63
Clerical workers	29
Service workers and shop/market sales workers	25
Agricultural and fishery workers	19
Production craftsmen and related workers	26
Plant and machine operators and assemblers	25
Cleaners, laborers and related workers	11

SSOC = Singapore Standard Occupation Classification, 2000
SOPS = Singapore Occupational Prestige Score
Source: Chiew et. al. (1991)

Table A.8: Descriptive Statistics of Key Variables

Variable	All		Youth Population in 2002
	N=271	%	N=669,529
Ethnicity			
Chinese	216	79.7	78%
Malay	39	14.4	14%
Indian	14	5.2	7%
Others	2	0.7	1%
Gender			
Male	113	41.7	50%
Female	158	58.3	50%
Age Group			
23-26	167	61.6	54%
27-29	104	38.4	46%
Income			
Low (<=S$1,500)	57	21.0	-
Middle (S$1,501-3,000)	176	64.9	-
High (>S$3,001)	38	14.1	-
Education			
Primary & below	4	1.5	-
Secondary	82	30.3	-
Pre-U/Polytechnic	113	41.7	-
University & above	72	26.6	-
Occupational Class			
Unskilled	18	6.6	-
Low-skilled	43	15.9	-
Skilled	131	48.3	-
High-skilled	79	29.2	-

Source: National Youth Survey 2002. Ho & Yip (2003)

Figure A.1: Youth's and Parents' Incomes from NYS

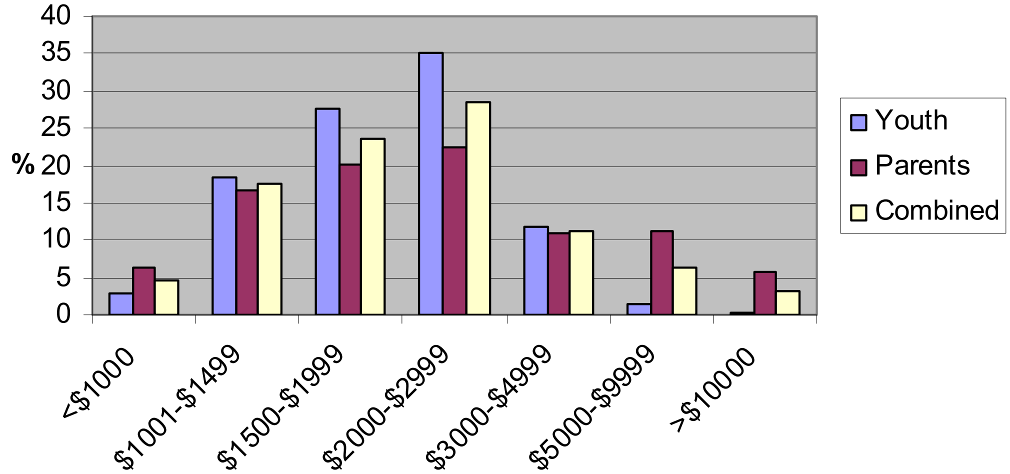


Figure A.2: Monthly Personal and Household Income from Singapore Census of Population 2000

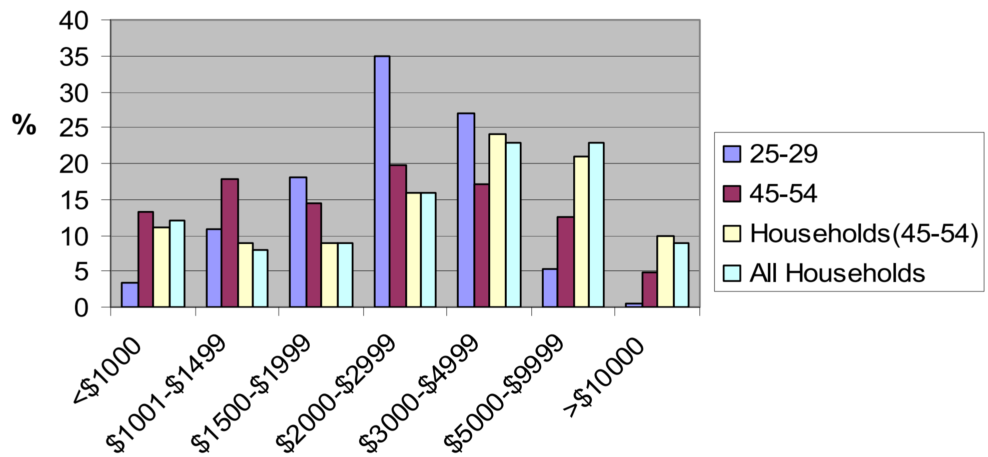


Figure A.3: Youth's and Parents' Educational Levels in NYS

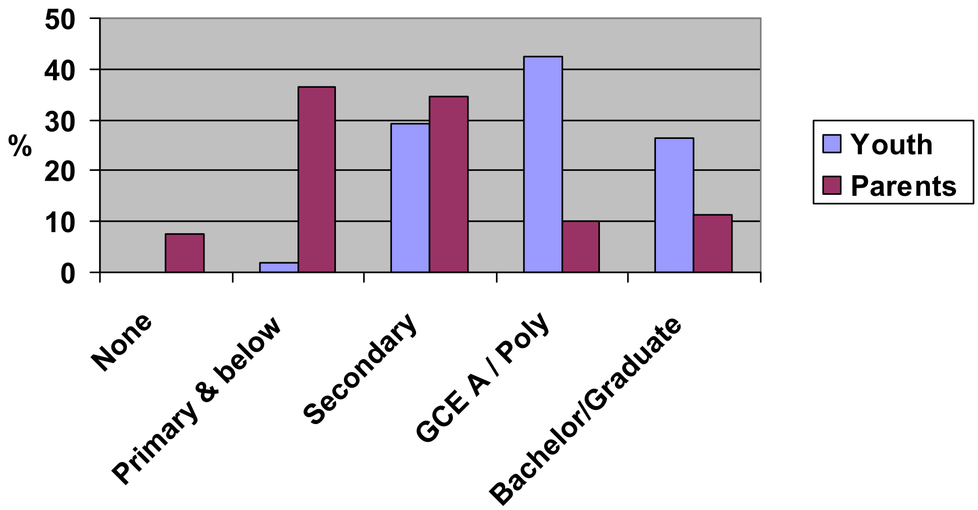


Figure A.4: Highest Educational Qualification attained from Singapore Census of Population 2000

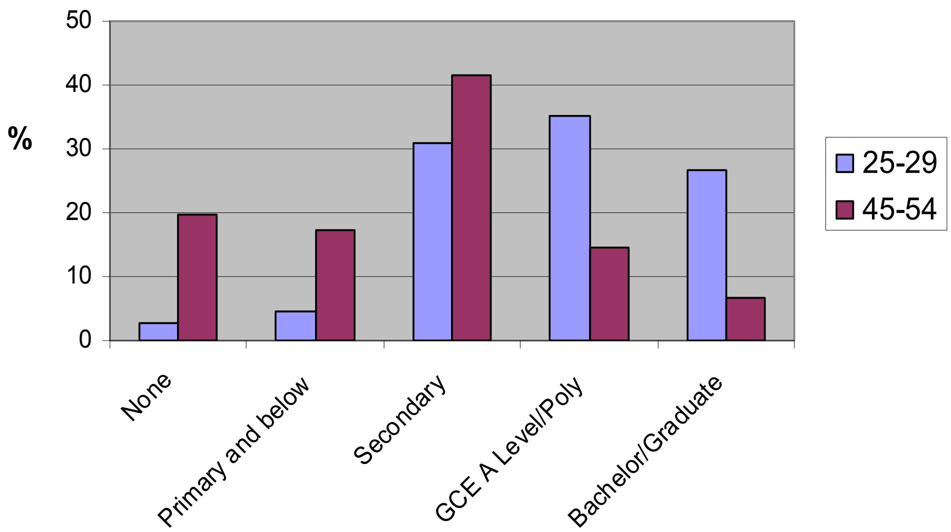


Figure A.5: Youth's and Parents' Occupational Class in NYS

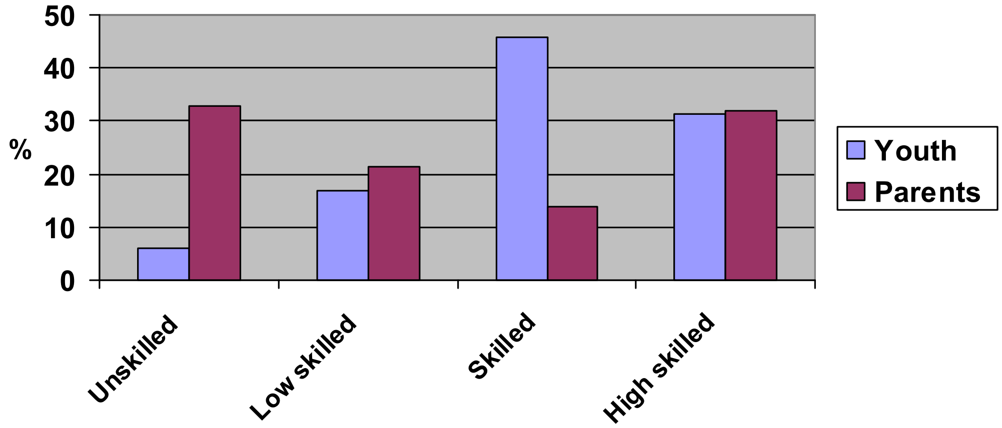
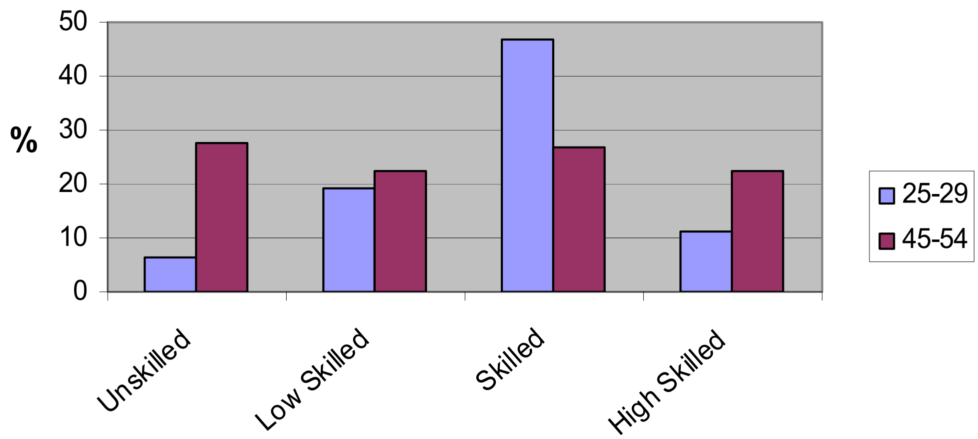


Figure A.6: Occupational Status from Singapore Census of Population 2000



High skilled: Legislators, senior officials; professionals
Skilled: Assoc. Professionals & technicians; Clerical workers
Low skilled: Service workers, production craftsmen
Unskilled: Plant & machine operators; Agricultural & fishery workers, Cleaners & laborers.[9]

[9] These occupational classes were self-categorized, and correspond to those in Chiew et. al. (1991)

Figure A.7: Age-earnings Profiles by Occupational Class from Report on Wages in Singapore 2002

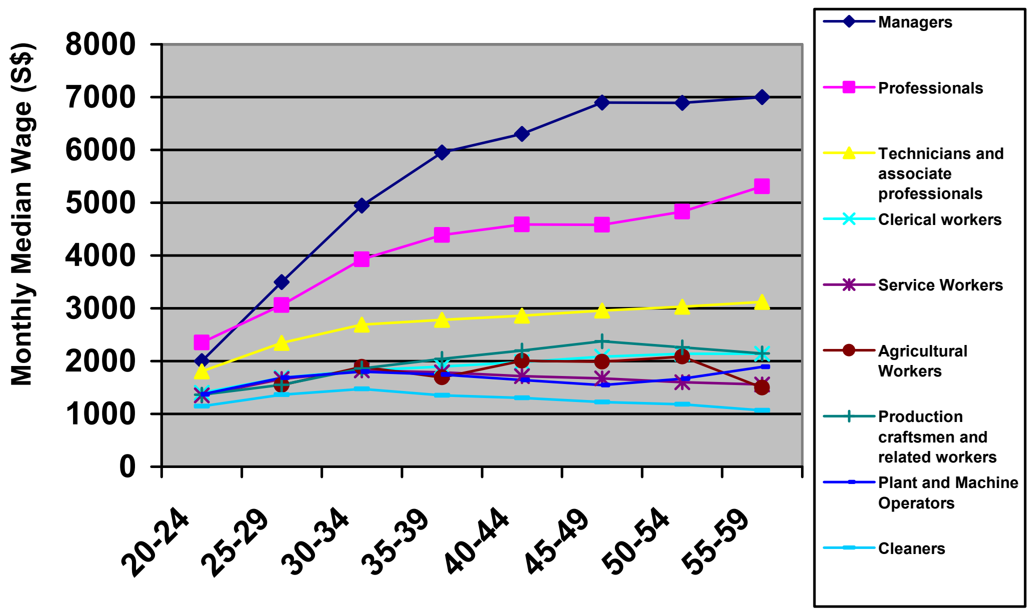
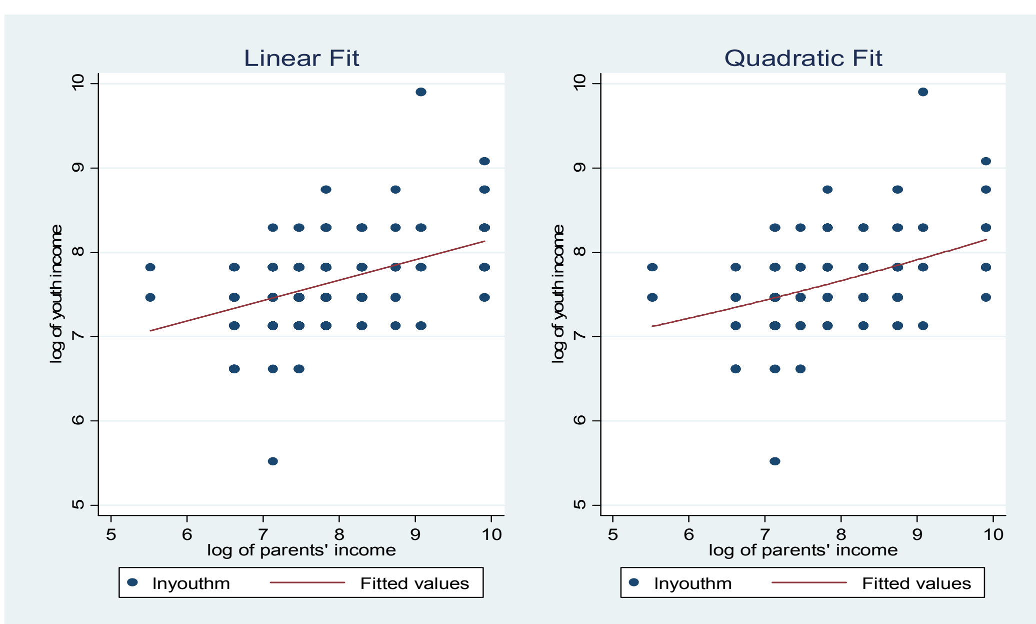


Figure A.8: Scatter Plot, Linear and Quadratic Fits of Log (Youth Income) and Log (Parental Income)



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