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"The Distribution of Male Wages in Brazil"

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The Distribution of Male Wages in Brazil: Some Stylised Facts

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Abstract

This paper examines the evolution of wage inequality in Brazil in the 1980s and 1990s . It tries to investigate the role played by changing economic returns to education and to experience over this period together with the evolution of within-group inequality. It applies a quantile regression approach on grouped data to the Brazilian case. Results using repeated cross-sections of a Brazilian annual household survey indicate that :
i) Male wage dispersion remained basically constant overall in the 1980's and 1990´s but has increased substantially within education and age groups.
ii) Returns to experience increased significantly over this period, with the rise concentrated on the iliterate/primary school group
iii) Returns to college education have risen over time, whereas return to intermediate and high-school education have fallen
iv) The apparent rise in within-group inequality seems to be the result of a fall in real wages, since the difference in wage levels has declined substantially over the period, especially within the high-educated sample.
v) Returns to experience rise with education.
vi) Returns to education rise over the life-cycle.
vii) Wage inequality increases over the life-cycle.
The next step in this research will try to conciliate all these stylised facts.

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1 - Introduction

There has recently been a renewed interest in the role of technological change in the labour market. This has been spurred by several events. Many comentators have pointed to a large increase in earnings inequality in Britain and in the U.S. (and to a lesser extent other European countries), for which technology is frequently seen as the major culprit.[1] The argument is that the rapid increase in skilled workers' relative remuneration, accompanied by the rise in education qualifications, drives fundamentally from a demand shock which would be associated with the computer revolution.

This paper is an attempt to investigate this issue in the Brazilian context. This is important for several reasons. One of the main features of the Brazilian economy is its extremely wide wage and income distribution. A study by Psacharopoulos (1991), for example, shows that among 56 countries in the world, Brazil is the most unequal. The proportion of income appropriated by the 10% richest families was about **50%** in Brazil in early 1980s, whereas the 40% poorest got only **7%**.[2] Also, Squire and Zou (1998) present new data on Gini coefficients which has Brazil on the top of the list with an average (over time) coefficient of **57.8** relative to a sample mean (s.d.) of **36.2 (9.2)**. Moreover, the important institutional differences between Brazil and most European and North American countries, especially its extremely high and inflation rates over the 1980s and the high proportion of employees in the informal sector of the economy, make a comparison of the Brazilian experience with labour market trends in Europe and U.S. worth investigating.

The level and dispersion of wages in a country at a point in time will in general depend on the distribution of characteristics of workers such as education, effort, experience, other observed and unobserved skills and on the returns to these characteristics. These returns will, in turn, depend on the distribution of the demand for these characteristics. Institutional factors like trade unions and minimum wages may also affect the wage structure. With respect to the evolution of wage inequality over time, it can

[1] See Freeman and Katz (1997) for some internacional comparisons and Johnson (1997) for an interesting explanation.
[2] The equivalent numbers for the U.S. were (**23%** and **17%**), for the UK (**23%** and **18%**), Sri lanka (**34%** and **16%**) and Nepal (**46%** and **12%**).

be thought to depend on time, experience and cohort effects (see Gosling *et al*, 1998). The time (or macro) effects include changes in economic environment, such as institutional factors, inflation and unemployment rates that affect the workforce as a whole. Increasing returns to education that affect all individuals at a point in time would enter under this heading. Experience effects would, for example, reflect an increasing wage dispersion over the life-cycle, together with an aging population. Finally, cohort effects reflect permanent changes in the composition of the population due to differences in the characteristics of new entrants vis-a-vis leavers in the labour market (such as the size of the cohort and the level, quality and inequality of schooling). For example, Gosling *et al* (1998), using UK data, find that wage dispersion increased for workers of younger cohorts (conditional on age and time effects) and that this may reflect an increasing diversification of education. Moreover, the authors show that returns to education increased for new cohorts and that wage dispersion tends to increase over the life-cycle, mainly for individuals with low levels of education.

There is an extensive literature on the reasons underlying the high level of income inequality in Brazil. The existing explanations range from the country's historical background to the educational composition of the workforce and institutional factors, such as labour market segmentation and discrimination (see Cacciamali, 1993, for a review). All in all, it seems inescapable to conclude that any reasonable explanation for the income and wage inequality in Brazil has to be linked to education. Brazil is a country with a high level of education inequality and the returns to education are also very high, as compared to other countries (see Lam and Levinson, 1992). Barros (1997) for example, estimates that education explained, ceteris paribus, from 35% to 50% of wage inequality in Brazil on average in the 1980s.[3]

There have also been marked increases in inequality in Brazil since the 1960's. Bonnelli and Ramos (1995) for instance, show that the Gini coefficient increased from **0.500** in 1960 to **0.568** in 1970, **0.580** in 1980 and **0.615** in 1990. There is much less agreement on the causes underlying this rapid rise in inequality. In a landmark study,

[3] Barros (1997) also estimates that the sector of activity is responsible, ceteris paribus, for about 15% of inequality in Brazil, that formal/informal segmentation for about 7%, that regional differences account for 2% to 5%, gender discrimination for about 5%, racial discrimination for 2%, and that 5% are returns to experience.

Langoni (1973) concludes that education was responsible for about 58% of the increase in inequality between 1960 and 1970[4]. Some other studies, however, emphasize the role of institutions like government wage policies, weakening of trade unions, etc. (see Cacciamali, 1993). More recently, some studies have played down the role of education in the increasing inequality, emphasing instead macroeconomic effects, such as inflation and gdp-growth.[5]

The main piece of Brazilian evidence emphasizing the role of cohort effects is Lam and Levinson (1992). The authors investigate the relationship between the distribution of years of schooling and income inequality in Brazil and document a significant rise in mean years of schooling in Brazil for more recent birth cohorts and a fall in the variance. This fact, together with an increasing residual variance and returns to schooling with age, means that wage inequality tends to increase with age in Brazil in a point in time.

This paper also intends to focus on the evolution of wage inequality in Brazil in 1980's . We intend to build upon Lam and Levison (1992) in order to understand the behaviour of the economic returns to education and to experience over time by relaxing the assumption that cohorts are perfectly substitutable to each other in the Brazilian economy. If, for example, technological improvements lead to differential returns to education between young and older workers, as new entrants into the labour market may be more vulnerable to changes in demand for labour, then returns to experience will change over time and this would be interpreted as a cohort effect. This has special significance if there are changes in the quantity, quality and inequality of education across generations (which, as we show below, is case in Brazil).

Ther main aim of this paper is to investigate the behaviour of the wage inequality in Brazil in the 1980s and 90s. With repeated cross-sections and an specification developed by MaCurdy and Mroz (1991) and used by Gosling *et al* (1998), it is possible, in principle, to disentangle de-trended time effects (constructed as to average zero over the sample period) from trend and life cycle effects, as determinants of the evolution of wage

[4] Of which 35% due to compositional changes and 23% to changing economic returns to education.

[5] Bonnelli and Ramos (1990) state that education is responsible for about 15% of the increase in inequality between 1977 and 1989 (mainly due to increasing returns). About 56% of the variation was left unexplained. Fishlow et al (1993), find that education differentials decreased from 1976 to 1981 and increased from 1981 to 1985 (especially for the college graduates). Lam and Levinsohn (1993) find that returns to schooling fell from 1976 to 1985, especially from 1976 to 1982.

inequality. Therefore, we intend to net out macro-effects and go deep into the structural causes of the rise in inequality in Brazil in the 1980s.

2- Econometric Methodology

As we saw above time, cohort and age effects may seem important in driving the increase in wage inequality. Unfortunately it is impossible to disentangle their separate effects, due to a fundamental identification problem. As Heckman and Robb (1985) point out, birth cohort (c) is completely determined by age (a) and a time trend (t):

$$c = t - a \qquad (1)$$

We try to model the wage equation in a parsimonious way, following MaCurdy and Mroz(1995) with functions of time, age and cohorts as follows:

$$lw = \alpha + A(a) + T(t) + C(c) + R(a,c,t) + u \qquad (2)$$

where the functions R are included to try and capture interactions between age, time and cohorts, like changing returns to experience over time. When exploring third order interactions between cohort, time and age:

$$A(a) = A_1 a + A_2 a^2 + A_3 a^3$$

$$T(t) = T_1 t + T_2 t^2 + T_3 t^3$$

$$C(c) = C_1 c + C_2 c^2 + C_3 c^3$$

$$R(a,c,i) = R_1 ai + R_2 at + R_3 it + R_4 ai^2 + R_5 ac^2 + R_6 ic^2 + R_7 it^2 + R_8 ci^2 + R_9 ti^2$$

we know that because of the identification problem, out of the 18 coefficients associated with third order terms, only 9 linear combinations of them can be identified. We therefore, choose as na equation to be taken to the data:

$$lw = \alpha + A_1 a + A_2 a^2 + A_3 a^3 + T_1 t + T_2 t^2 + T_3 t^3 + R_1 it + R_2 it^2 + R_3 t^2 i + u \qquad (3)$$

and the estimated parameters are in fact:

$$A_1 = (A_1 - K_1),$$

$$T_1 = (T_1 + K_1),$$

....

This fact must be kept in mind, when interpreting the results of the regressions. The error term in (3) include time effects:

$$u = u_{it} + \overline{u}_t \qquad (4)$$

that are constructed to be orthogonal to the age and trend functions, that is, they include no trends All trends in the data will then be reflected in the age and trend variables.

In the empirical investigation below we will break the data into education, year and age cells using the fact that our variables of interest are all discrete. We then compute different sample percentiles of the wage distribution and estimate (weighted) linear regression models on the grouped data for each quantile and education group separately, as in Chamberlain (1993). If all percentiles evolve in the same way (apart form an intercept shift), then the changing dispersion of wages can be explained by changing prices and/or composition of observed skill characteristics. The median defines the location of the distribution and the percentiles around it describe the changes in dispersion.

We therefore have:

$$lw^q = \alpha^q + A^q(a) + T^q(t) + C^q(c) + R^q(a,c,t) + u^q \qquad (5)$$

The set of functions T^q for each quantile will measure differences in wages over time. The difference in these functions between the top and bottom of the distribution will capture trend effects on the within-groups dispersion of wages. The difference across education groups for each quantile will measure changes in the returns to education over time. The

functions A^q measure how the wage distribution changes as each education group gets older. The changes in the median will reflect experience effects and differential rates of learning by doing will mean that the variance of wages will increase with age (see Mincer, 1974 and Farber and Gibbons, 1997). Common shocks to the wage distribution $\bar{u}_t$ are the same for each educational group regardless of age, such as macroeconomic effects common to all individuals at any point in time.

We proceed as follows: We first choose within each cell a population characteristic of interest and estimate it using the corresponding sample characteristic. We estimate the median, $10^{th,}$ 25^{th}, 75^{th} and 90^{th} percentiles for each age, year and education cell. This equivalent to using the full sample to regress wages on all education year and age interactions. The percentiles are asymptotically normally distributed (see Koenker and Portnoy, 1998). The variance of these estimated order statistics is given by

$$V(q) = \frac{q(1-q)}{f(q)^2} \qquad (6)$$

We estimate f(q) (conditional density) using a Gaussian Kernel with bandwith equal to half the standard deviation of wages for each cell.

We then try to impose some structure on the wage distribution by means of a minimum distance estimator. The minimum distance procedure chooses β such as to minimise:

$$(q-\beta Z)'V(q)^{-1}(q-\beta Z) \qquad (7)$$

where q are the estimated order statistic and Z is a set of linear restrictions.
Under the null that the restrictions are valid, the minimised value follows a chi-squared distribution with degrees of freedom equal to the number of restrictions. As this is like weighted least squares, the grouped regression procedure will give us consistent estimates and all we have to do to construct the test statistic is to sum the weighted squared residuals, i.e. the empirical percentiles minus the age and trend effects, minus the orthogonal time effects.

3 - Data

In this paper we use a particularly rich data set, consisting of repeated cross-sections of an annual household survey, conducted every September by the Brazilian Census Bureau. It consists of around 125,000 annual individual level data. From the original data we kept only male (to avoid the usual composition problems due to changes in female participation), with positive hours worked in the reference week, positive monetary remuneration, with between 25 and 55 years of age. The final sample have 706,782 observations in the low education group (0 to 4 years of schooling) 214,077 in the intermediate one (5 to 8), 161,355 in the (some) high school group and 110,883 in the (some) college one. The sample period ranges from 1977 to 1996.

The main variable used in this analysis is real hourly wage, defined as normal labour income in the main job in the reference month normalised by normal weekly working hours. The nominal wage was deflated using the Brazilian consume price index (IPCA) and took into account the change in currency that took place in 1986.

4 - Results

Tables **1 to 4** present the main results of the paper. Although the results are best interpreted in terms of the figures presented in the end of the paper, some points deserve mentioning. Firstly, all coefficients seem to have been precisely estimated. Secondly, there are important differences both among the different percentiles within each education group and across different education groups. Thirdly, the coefficients on the interactions between trend and age tend to be significant in all education groups and percentiles, which means that returns to experience are seem to be changing in the sample period. Finally, the Chi-squared test tends to reject the restrictions in all specifications, which raises serious doubts about the explaining power of the restricted model.

The examination of the figures tell a very interesting story. Figures **1** and **2** plot the predicted median wages for the first and fourth education group respectively, for different age groups. The model seems to predict quite well the evolution of wages in Brazil over the

sample period. It is also interesting to note that real wages have fallen dramatically over time for all education groups. Figures **3** and **4** do the same for the 90^{th} percentile and the results are similar though the fit is a not quite as good. Figures **5** and **6** show that, although we are able to follow the evolution of the 90/10 differential of (log) wages quite closely for the lowest education group, the results are poor if one consider the college group, especially at higher ages. This is probably the result of the small sample size in these cells.

Graph **7** plots the evolution of the trend effect on wages (abstracted from cyclical effects), for those with 44 years of age. It seems clear that real wages have fallen for all groups, but the fall was markedly lower for the highest eudcation group. This resulted, as shown in figure **8,** in a rise in the returns to college education in Brazil, together with a fall in the returns to intermediate and high school education. This has taken place across the wage distribution, as shown by figures **9** and **10.**

On the evolution of the wage inequality over time, figures **11** and **12** show that the 90/10 ratio of smoothed predicted wages has increased in Brazil over the sample period withing education groups, apart from the intermediate education group. To check whether this rise in inequality is the result of a rise in the spread or a fall in the median, figures **13** and **14** plot the predicted wages from a regression of the **level of wages** on age and trend. The results are impressive, as it seems that the absolute level of inequality has decreased for the higher education groups and remained roughly constant for the less educated.

Turning now to the age effects, Figure **15** shows that there are important interactions between education and experience, as evidenced by the significant differences in the age profiles across education goups. Returns to experience are higher for the more educated. This is also reflected in figure **16,** which shows that the returns to education tend to increase over the life cycle. The results of the interactions between age and trend are plotted in figures **17** to **20.** It seems that returns to experience have risen mostly for the low education group, whilst have risen from 1977 to 1987 and then fallen in 1996 for the other groups.

Figures **21** to **24** show that the returns to experience vary dramatically across percentiles, especially for the low education groups. Significantly, for the high education groups, there is almost no variation. Finally, figure **25** shows that inequality tends to increase markdly over the life cycle, that is, age is associated with within-group inequality

These results are evidence that the wage behaviour over the life cycle in Brazil is similar to the UK, notwithstanding the differences between the two countries in various aspects.

4 - Conclusions

To be concluded

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Table 1 – Education between 0 and 4 years of schooling

	10th	25th	50th	75th	90th
Constant	-0,523	-0,082	0,348	0,806	1,202
	0,031	*0,025*	*0,027*	*0,027*	*0,026*
Trend	0,565	0,180	0,017	-0,078	-0,064
	0,091	*0,074*	*0,082*	*0,081*	*0,081*
Squared trend	-1,316	-0,822	-0,672	-0,462	-0,418
	0,103	*0,085*	*0,094*	*0,092*	*0,093*
Cubic trend	0,472	0,311	0,271	0,187	0,167
	0,036	*0,030*	*0,033*	*0,033*	*0,033*
Age	0,182	0,181	0,299	0,384	0,458
	0,058	*0,046*	*0,051*	*0,051*	*0,051*
Squared age	-0,069	-0,060	-0,103	-0,125	-0,120
	0,039	*0,032*	*0,035*	*0,035*	*0,035*
Cubic age	0,005	0,003	0,005	0,008	0,006
	0,008	*0,006*	*0,007*	*0,007*	*0,007*
Trend * Age	0,037	0,051	0,146	0,148	0,113
	0,052	*0,042*	*0,047*	*0,046*	*0,047*
Trend * Squared age	-0,016	-0,014	-0,020	-0,018	-0,011
	0,012	*0,010*	*0,011*	*0,011*	*0,011*
Squared trend * Age	0,019	0,013	-0,016	-0,021	-0,019
	0,019	*0,016*	*0,018*	*0,018*	*0,019*
Chi-Squared (632)	1239	786	1065	1109	1331

Table 2 – Education between 5 and 8 years of schooling

	10th	25th	50th	75th	90th
Constant	0,042	0,399	0,825	1,266	1,696
	0,024	*0,025*	*0,023*	*0,024*	*0,029*
Trend	0,292	0,256	0,271	0,197	0,049
	0,080	*0,079*	*0,076*	*0,078*	*0,091*
Squared trend	-1,111	-1,092	-0,996	-0,837	-0,662
	0,091	*0,089*	*0,086*	*0,088*	*0,101*
Cubic trend	0,441	0,441	0,387	0,321	0,296
	0,031	*0,031*	*0,029*	*0,030*	*0,035*
Age	0,331	0,498	0,520	0,593	0,662
	0,052	*0,052*	*0,051*	*0,052*	*0,061*
Squared age	-0,037	-0,132	-0,108	-0,116	-0,137
	0,038	*0,038*	*0,036*	*0,038*	*0,044*
Cubic age	-0,018	-0,002	-0,004	-0,004	0,000
	0,008	*0,008*	*0,008*	*0,008*	*0,009*
Trend * Age	0,099	0,157	0,111	0,055	0,038
	0,050	*0,051*	*0,048*	*0,050*	*0,059*
Trend * Squared age	0,036	0,036	0,031	0,041	0,043
	0,012	*0,012*	*0,011*	*0,012*	*0,014*
Squared trend * Age	-0,089	-0,115	-0,089	-0,074	-0,068
	0,020	*0,020*	*0,019*	*0,020*	*0,023*
Chi-Squared (632)	995	785	776	794	965

Table 3 – Education between 9 and 11 years of schooling

	10th	25th	50th	75th	90th
Constant	0,419	0,863	1,312	1,808	2,214
	0,036	*0,030*	*0,028*	*0,030*	*0,026*
Trend	0,034	-0,010	0,019	-0,104	-0,191
	0,110	*0,094*	*0,088*	*0,091*	*0,103*
Squared trend	-0,875	-0,718	-0,644	-0,453	-0,299
	0,120	*0,104*	*0,098*	*0,101*	*0,113*
Cubic trend	0,375	0,296	0,256	0,187	0,137
	0,041	*0,035*	*0,033*	*0,033*	*0,038*
Age	0,745	0,757	0,815	0,842	0,907
	0,069	*0,060*	*0,056*	*0,059*	*0,065*
Squared age	-0,221	-0,215	-0,209	-0,222	-0,255
	0,049	*0,042*	*0,040*	*0,042*	*0,046*
Cubic age	0,015	0,016	0,012	0,017	0,025
	0,011	*0,010*	*0,009*	*0,009*	*0,010*
Trend * Age	-0,085	-0,073	-0,134	-0,121	-0,103
	0,068	*0,059*	*0,056*	*0,058*	*0,064*
Trend * Squared age	0,045	0,028	0,031	0,027	0,023
	0,015	*0,014*	*0,013*	*0,014*	*0,015*
Squared trend * Age	-0,038	-0,019	0,009	0,013	0,002
	0,027	*0,024*	*0,022*	*0,023*	*0,025*
Chi-Squared (632)	1077	734	698	751	951

Table 4 – Education more than 12 years of schooling

	10^{th}	25^{th}	50^{th}	75^{th}	90^{th}
Constant	0,937	1,393	1,961	2,515	2,902
	0,041	*0,030*	*0,035*	*0,034*	*0,036*
Trend	-0,011	-0,046	-0,243	-0,561	-0,805
	0,124	*0,113*	*0,100*	*0,097*	*0,103*
Squared trend	-0,657	-0,553	-0,354	-0,071	0,393
	0,141	*0,125*	*0,111*	*0,108*	*0,114*
Cubic trend	0,288	0,234	0,174	0,027	-0,066
	0,049	*0,043*	*0,039*	*0,038*	*0,040*
Age	1,106	1,216	1,215	1,106	1,157
	0,080	*0,060*	*0,067*	*0,066*	*0,069*
Squared age	-0,446	-0,500	-0,510	-0,448	-0,498
	0,056	*0,050*	*0,045*	*0,045*	*0,047*
Cubic age	0,054	0,065	0,068	0,059	0,071
	0,012	*0,011*	*0,010*	*0,009*	*0,010*
Trend * Age	-0,048	-0,071	-0,039	-0,008	0,008
	0,076	*0,068*	*0,062*	*0,061*	*0,065*
Trend * Squared age	0,052	0,040	0,037	0,029	0,032
	0,018	*0,016*	*0,015*	*0,014*	*0,016*
Squared trend * Age	-0,052	-0,017	-0,020	-0,015	-0,027
	0,030	*0,027*	*0,024*	*0,023*	*0,025*
Chi-Squared (632)	989	836	764	746	997

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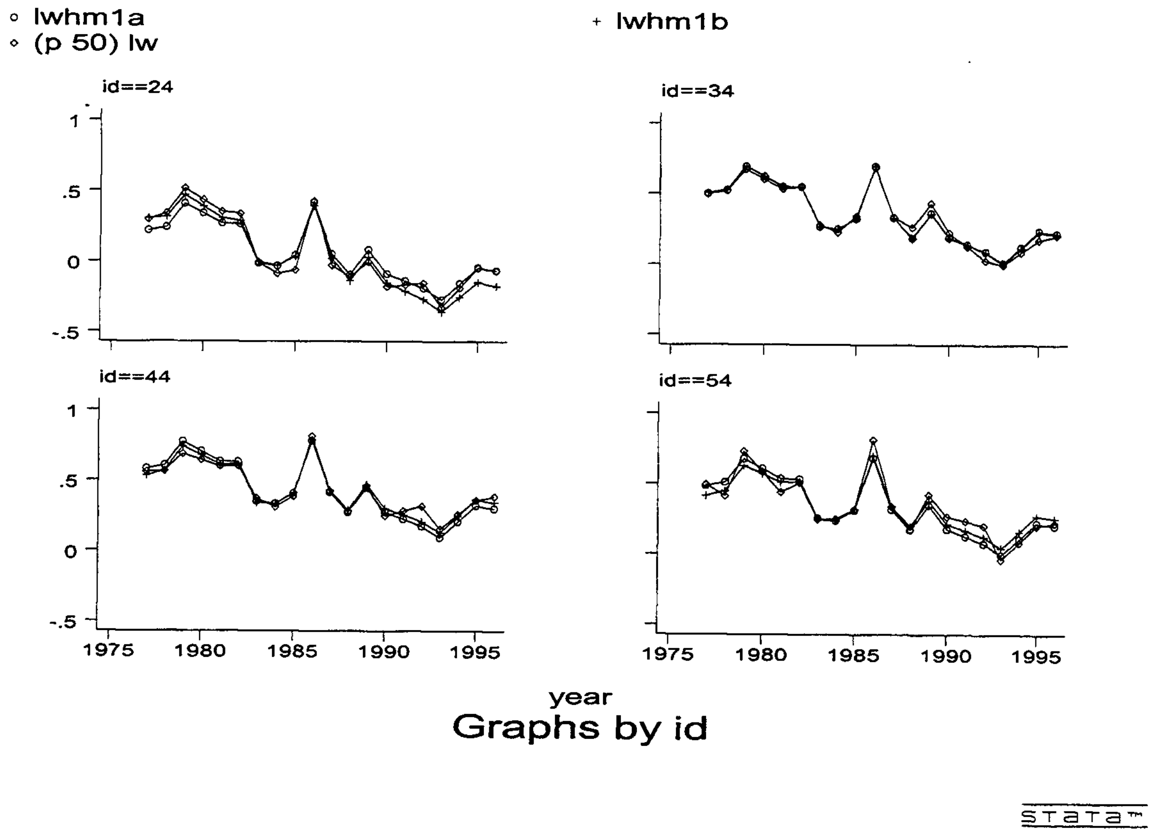

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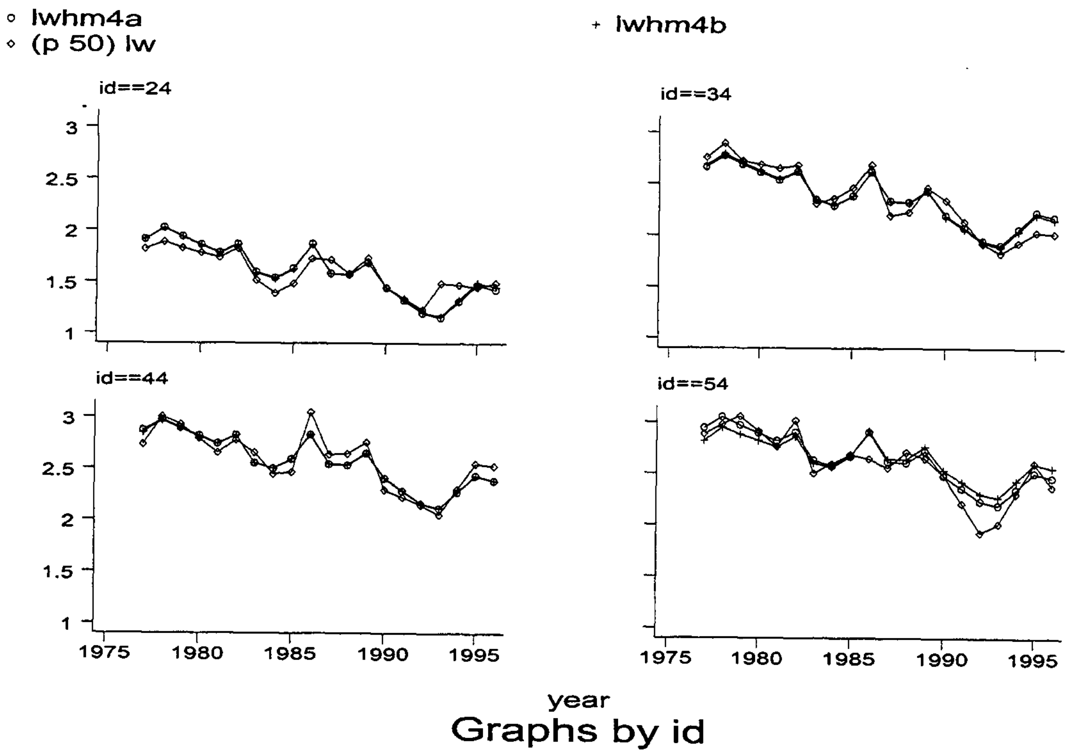

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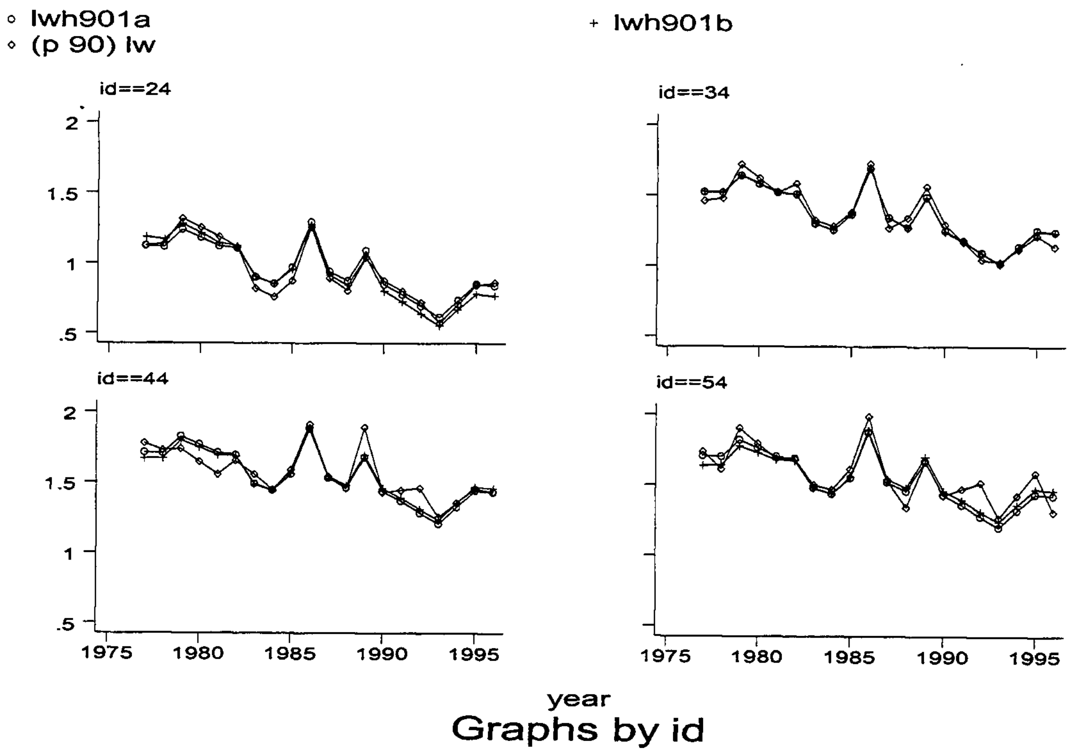
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1
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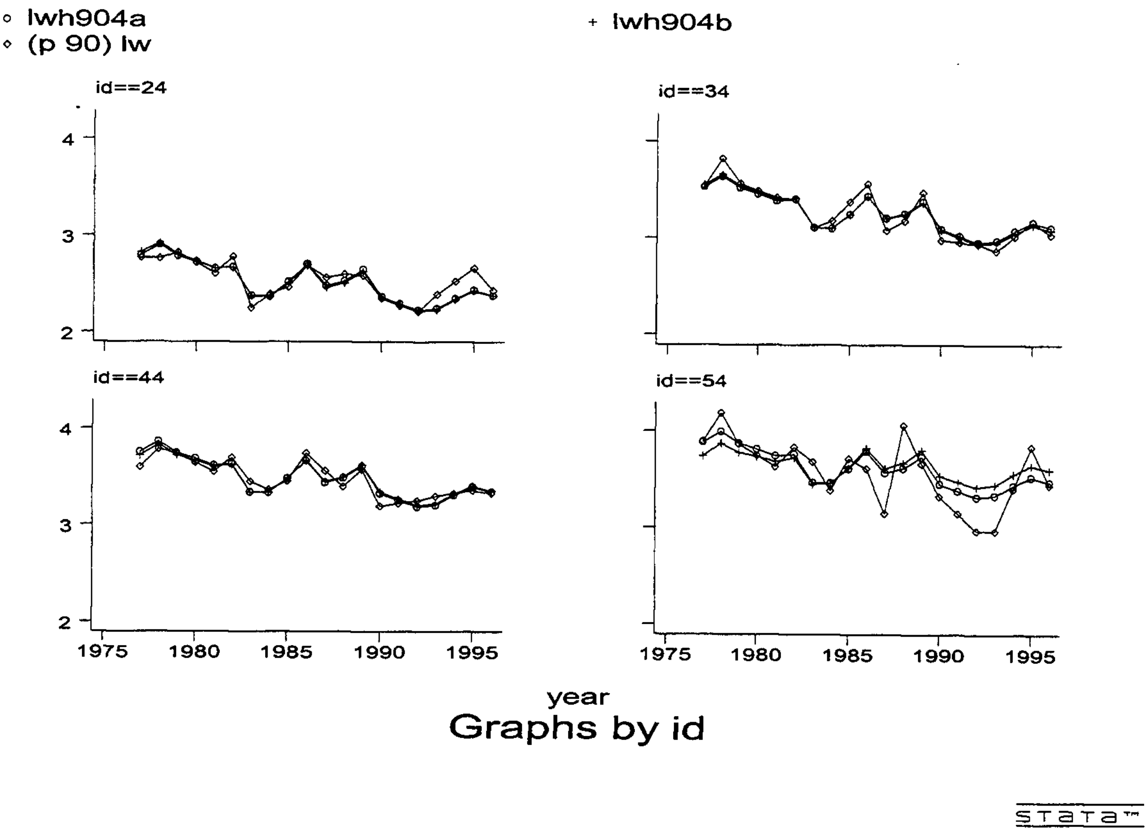
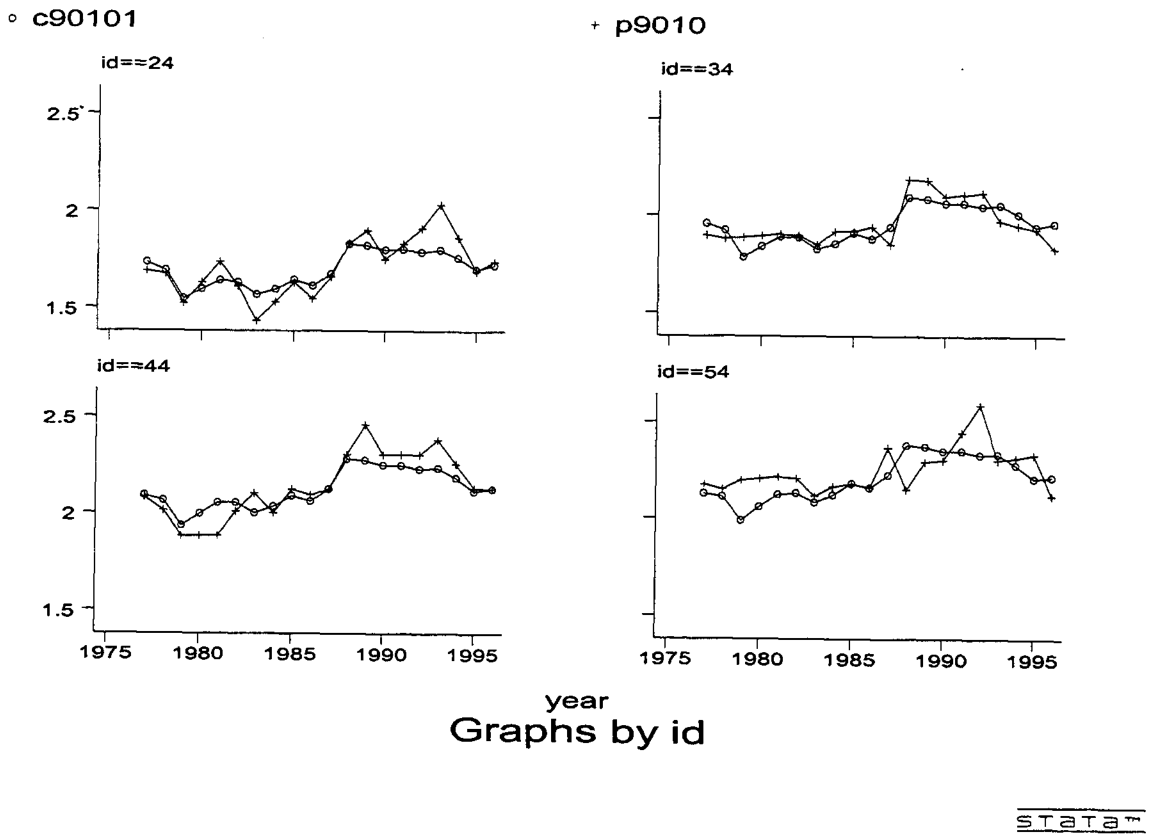
1975
1980
1985
1990
1995
year
Graphs by id

STATA™

4

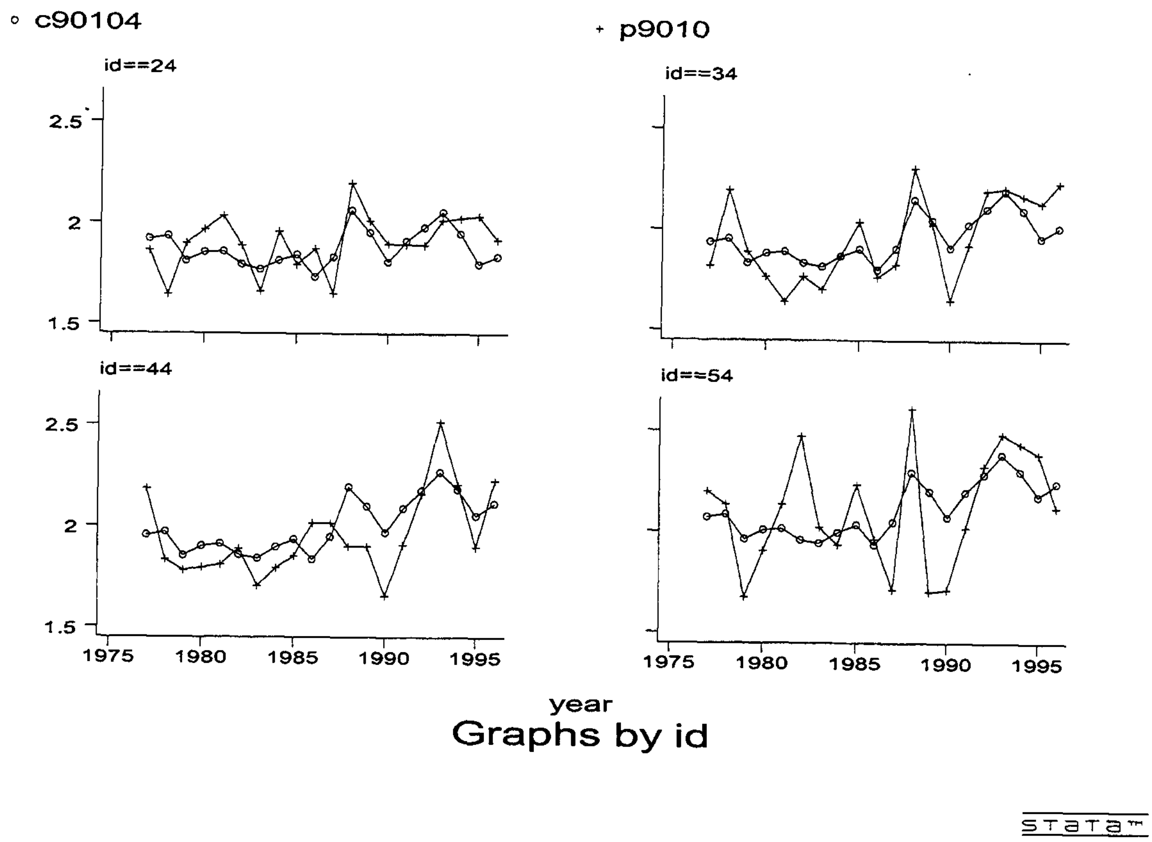

lwh904a
(p 90) lw
lwh904b
id==24
id==34
id==44
id==54
4
3
2
1975
1980
1985
1990
1995
year
Graphs by id

5



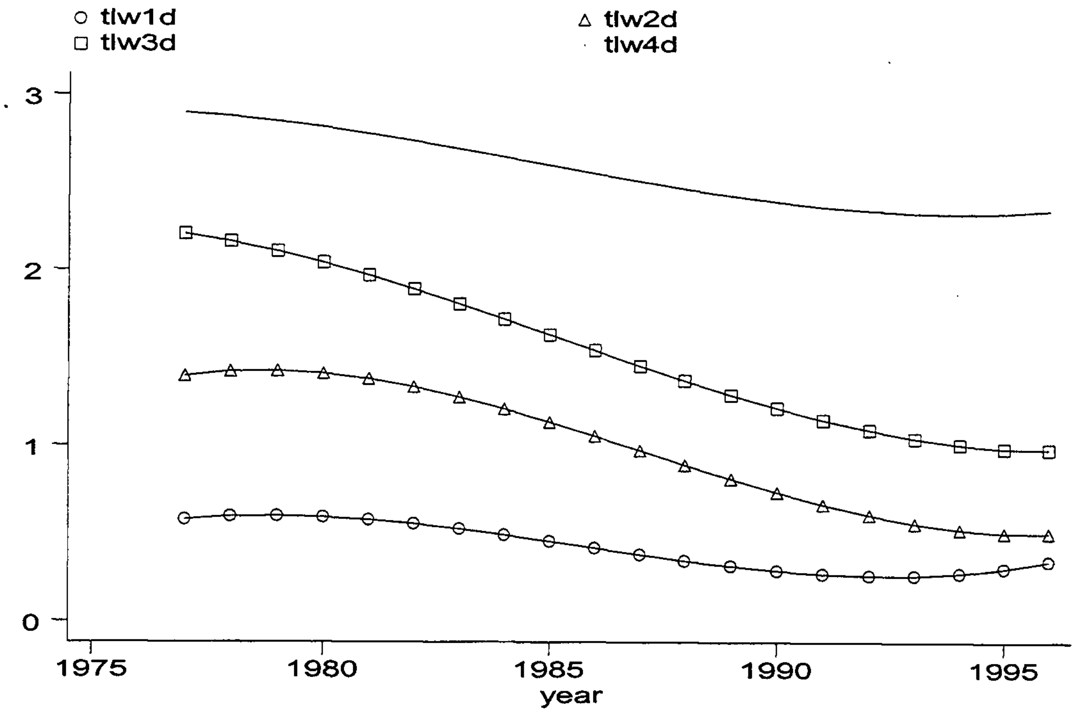
c90101
p9010
id==24
id==34
id==44
id==54
2.5
2
1.5
1975
1980
1985
1990
1995
year
Graphs by id
stata™

6



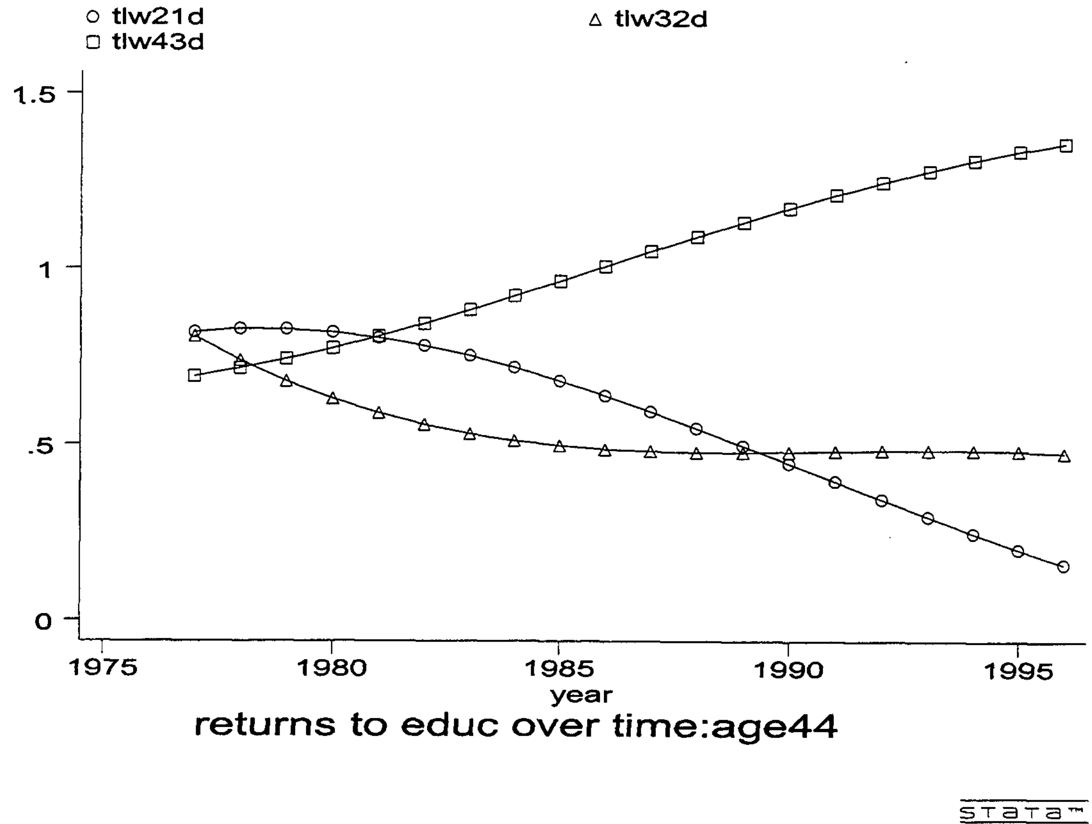
c90104
p9010
id==24
id==34
id==44
id==54
2.5
2
1.5
1975
1980
1985
1990
1995
year
Graphs by id
STATA™

7

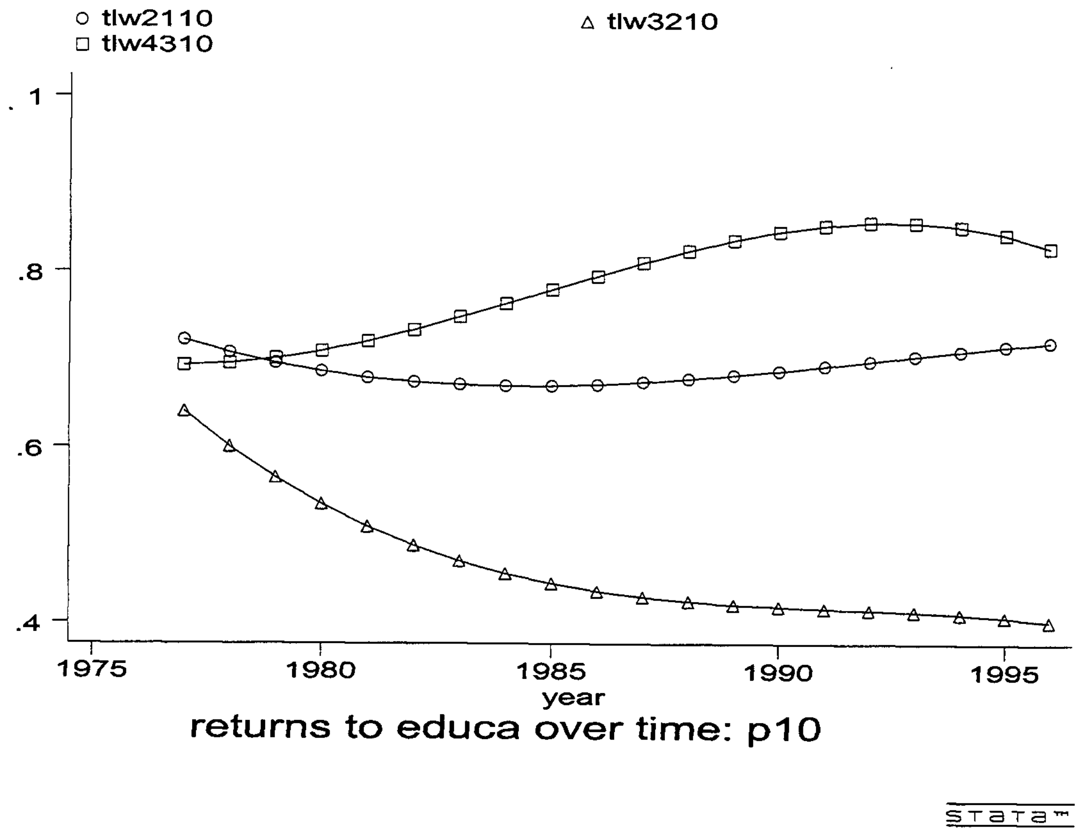


wages over time:age44

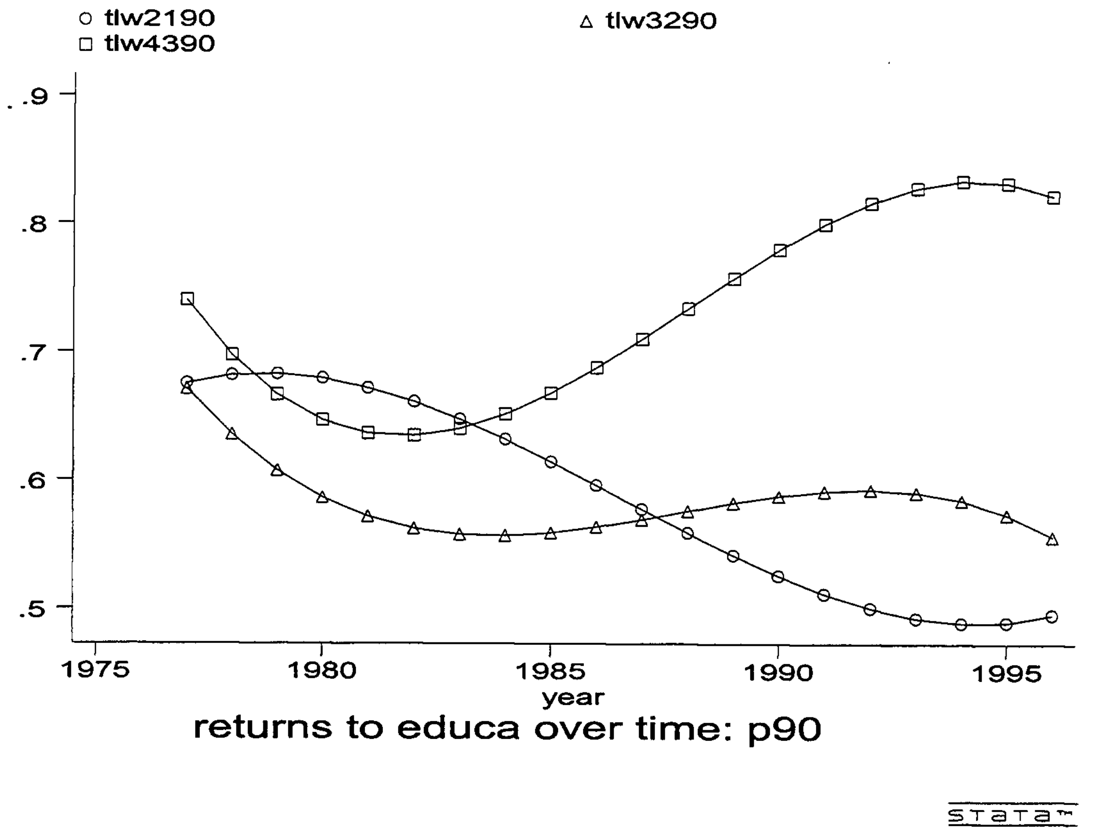
(8)



tlw21d
tlw32d
tlw43d
1.5
1
.5
0
1975
1980
1985
1990
1995
year
returns to educ over time:age44
stata™

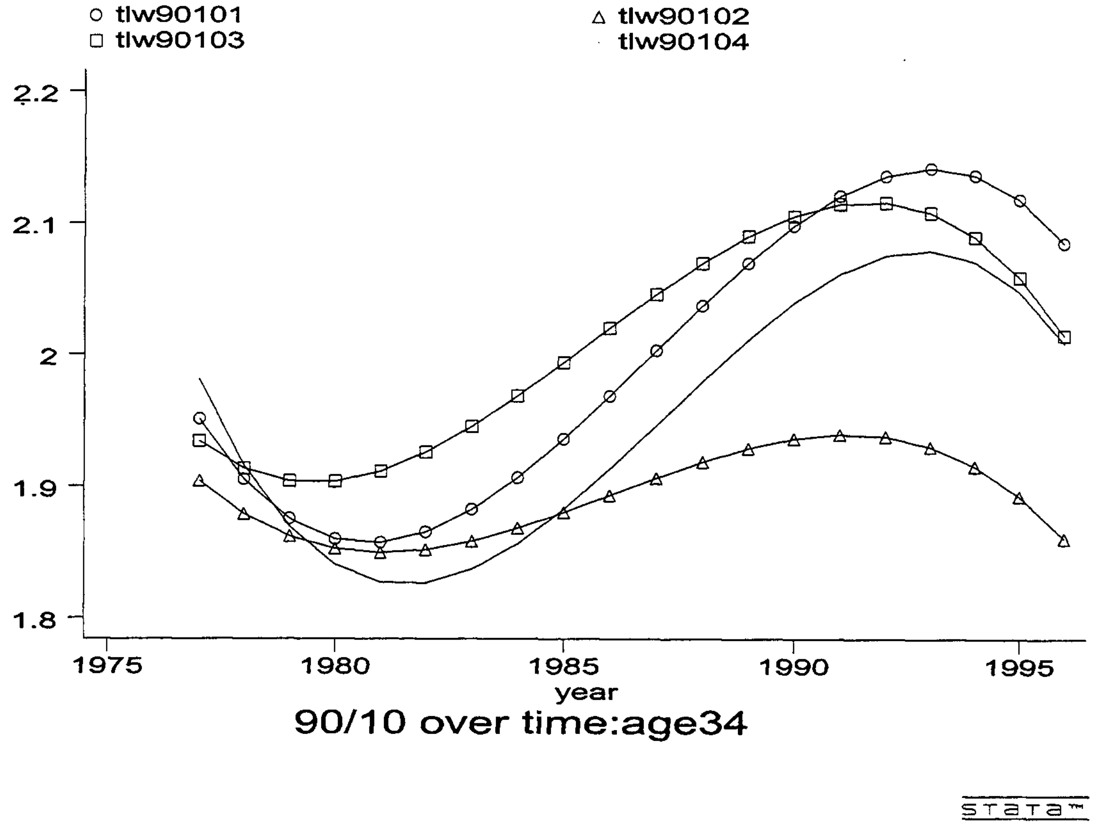

tlw2110
tlw4310
tlw3210
1
.8
.6
.4
1975
1980
1985
1990
1995
year
returns to educa over time: p10
stata

10

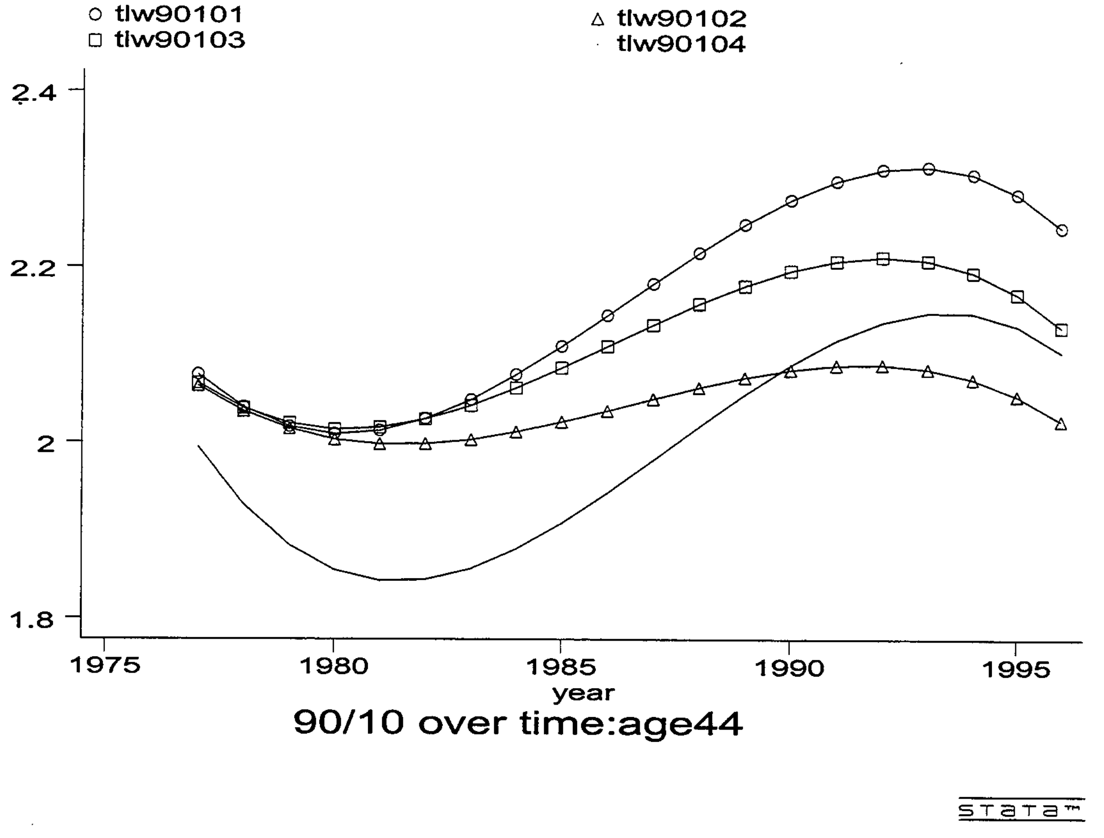


returns to educa over time: p90

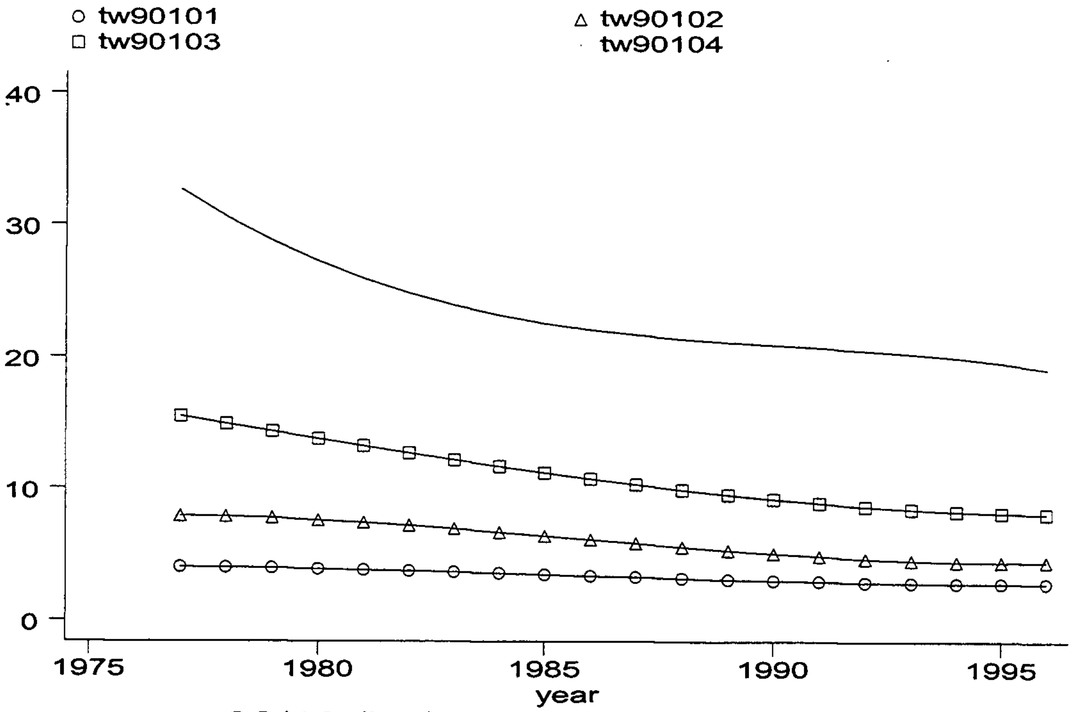
11


tlw90101
tlw90102
tlw90103
tlw90104
2.2
2.1
2
1.9
1.8
1975
1980
1985
1990
1995
year
90/10 over time:age34
stata

12

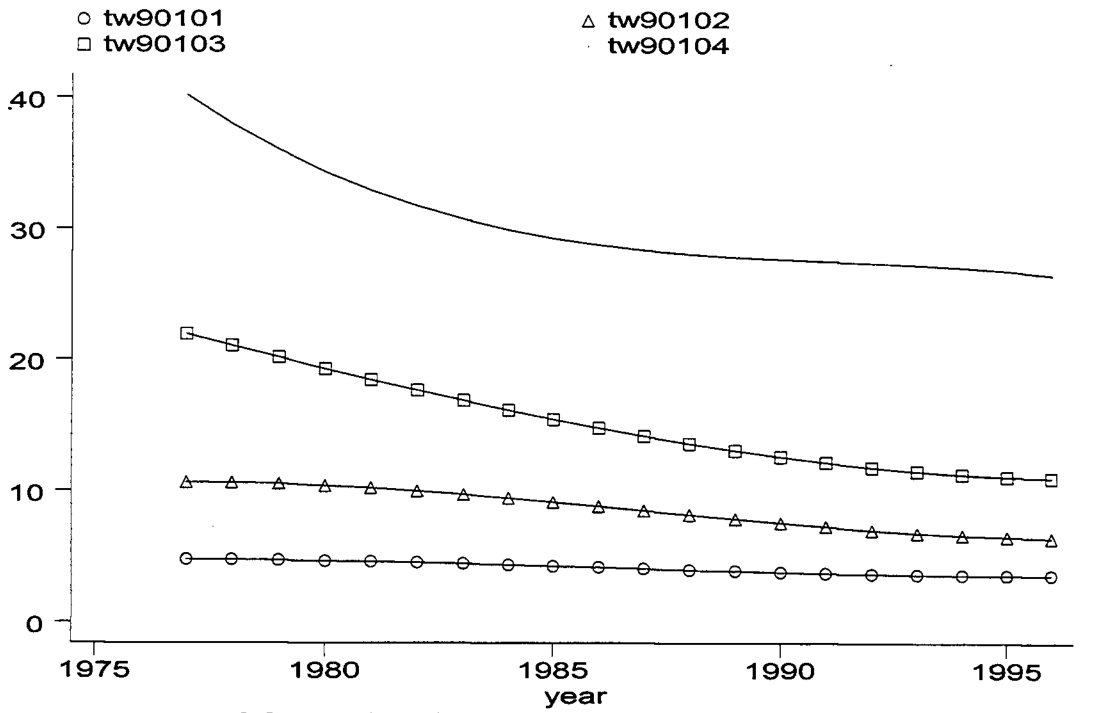

tlw90101
tlw90103
tlw90102
tlw90104
2.4
2.2
2
1.8
1975
1980
1985
1990
1995
year
90/10 over time:age44
stata™

(13)



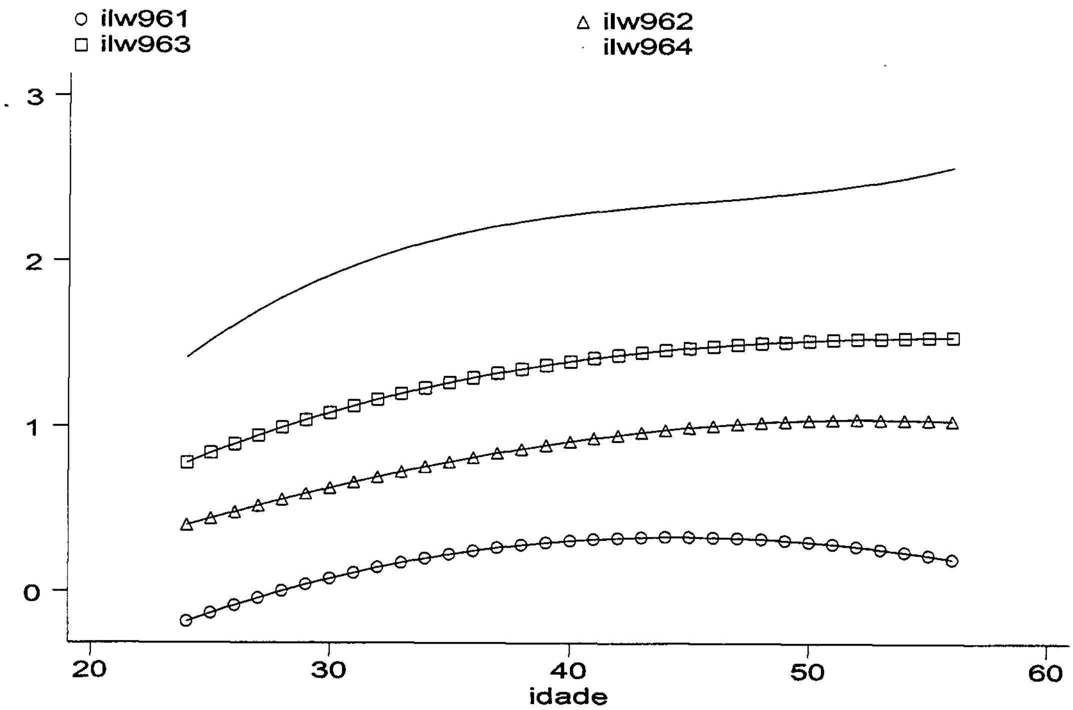
90/10 (lev) over time:age34

STATA™

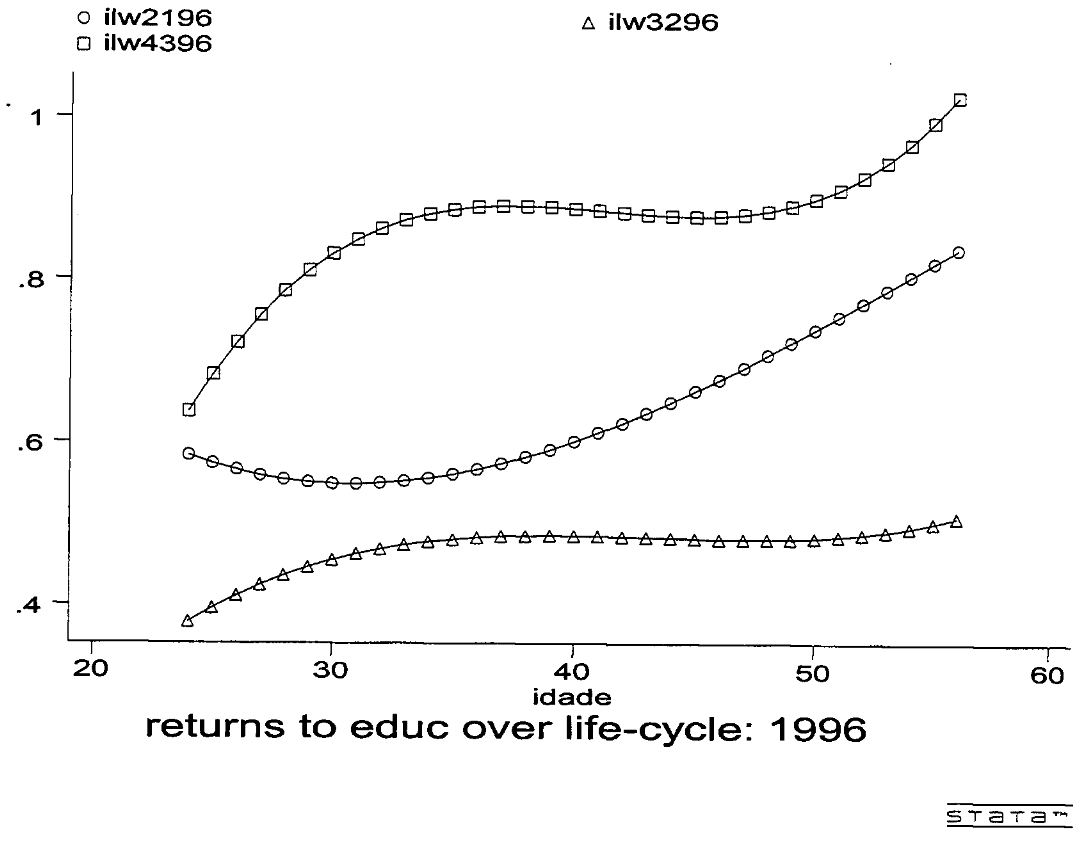


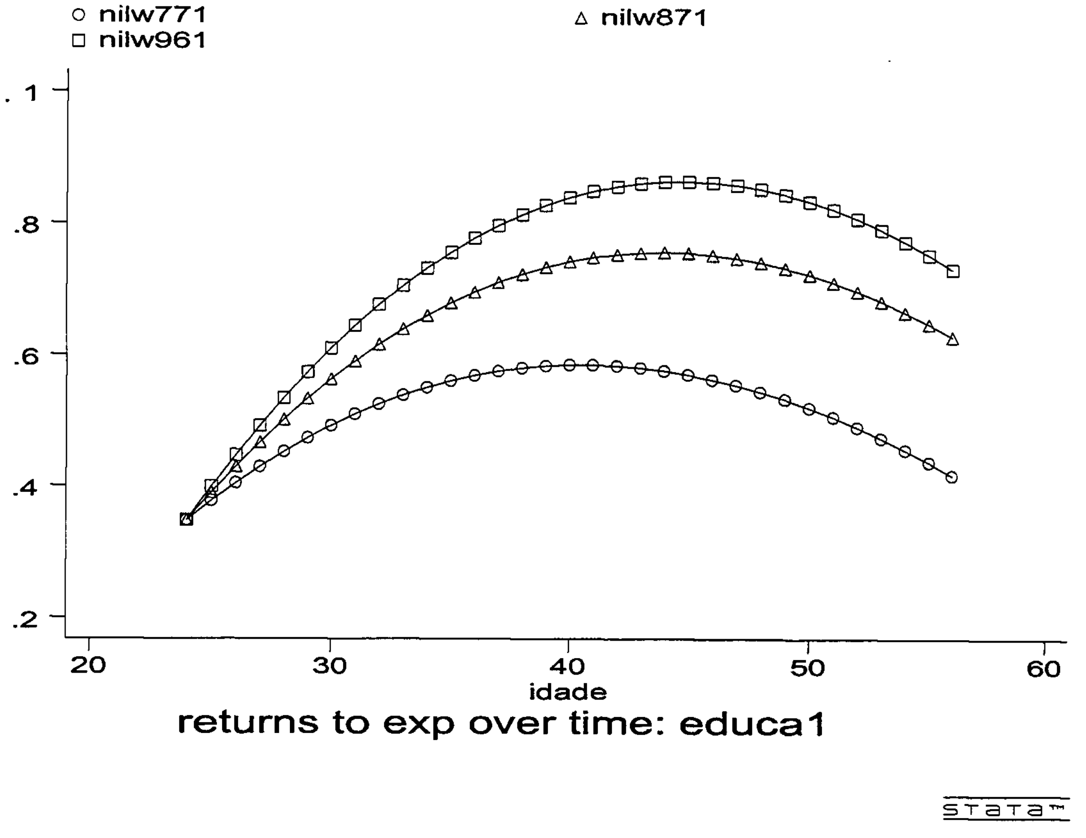
90/10 (lev) over time:age44

STATA™

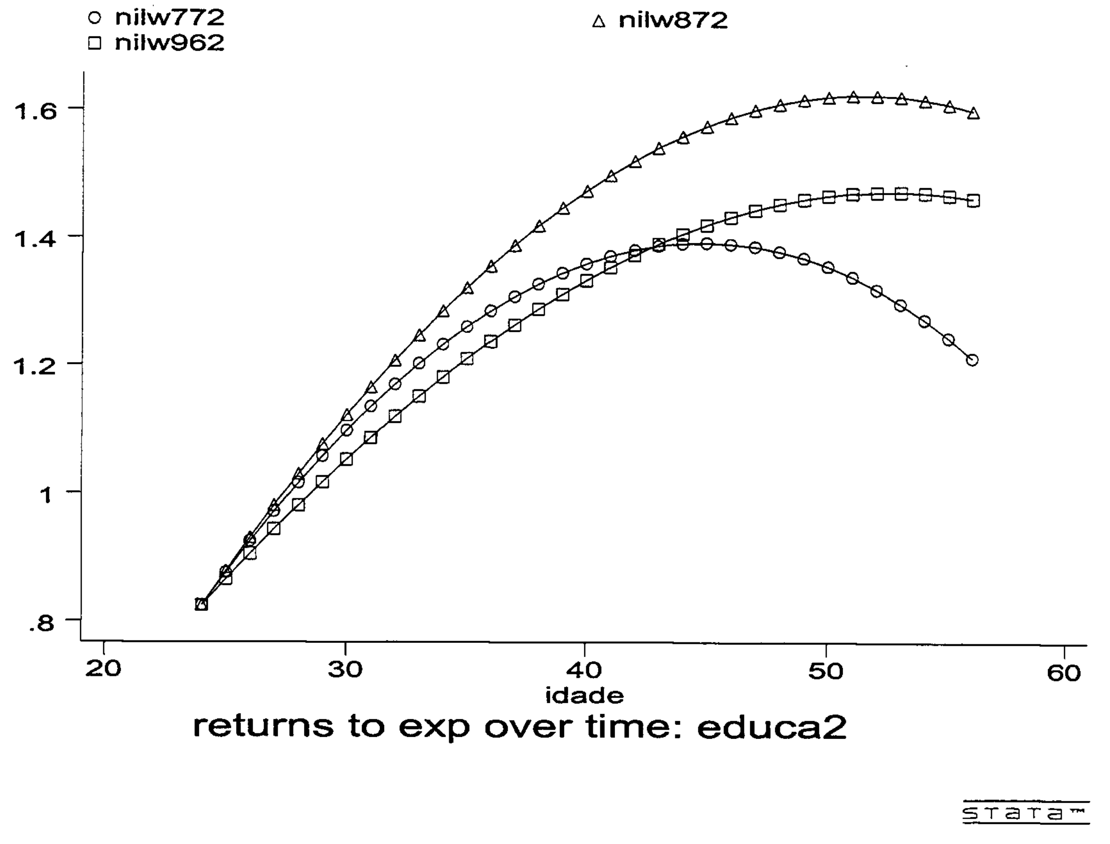


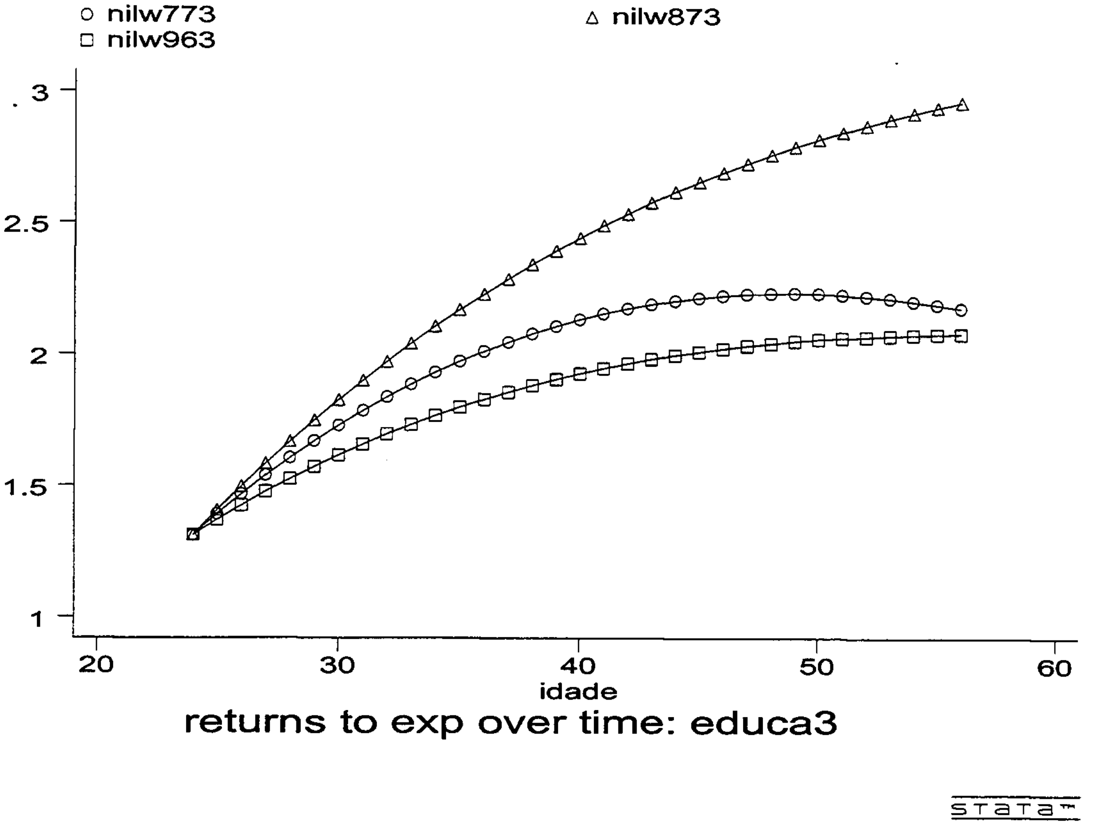
returns to exp: 1996

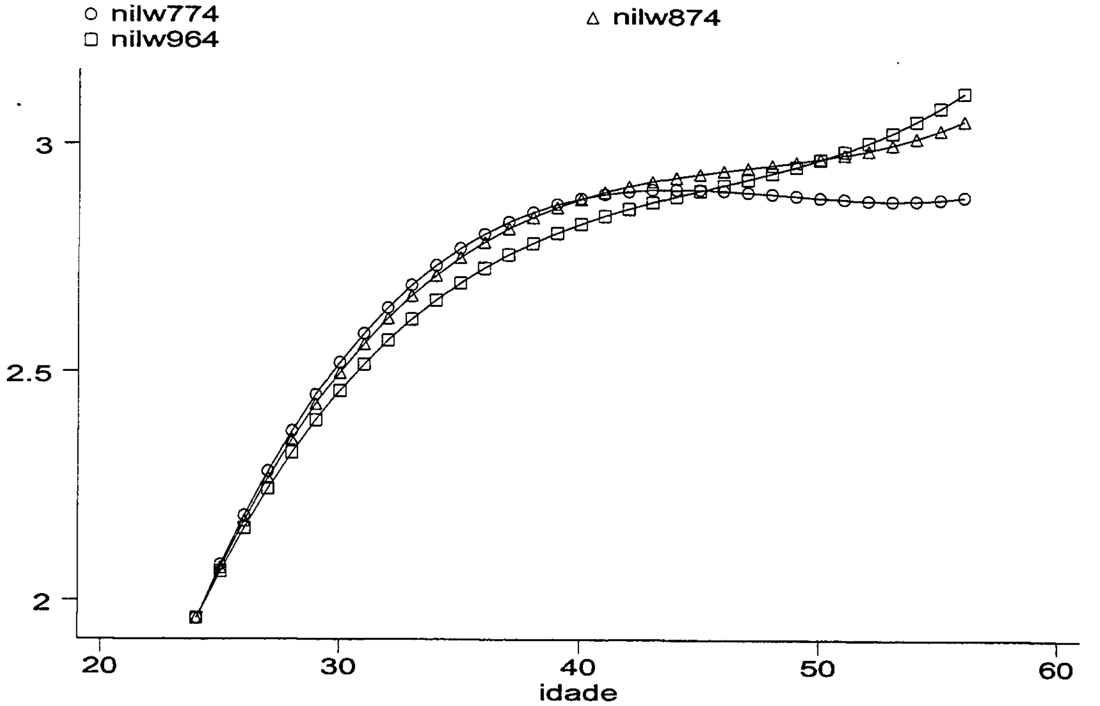

ilw2196
ilw4396
ilw3296
1
.8
.6
.4
20
30
40
50
60
idade
returns to educ over life-cycle: 1996
Stata™


nilw771
nilw871
nilw961
1
.8
.6
.4
.2
20
30
40
50
60
idade
returns to exp over time: educa1
STATA™

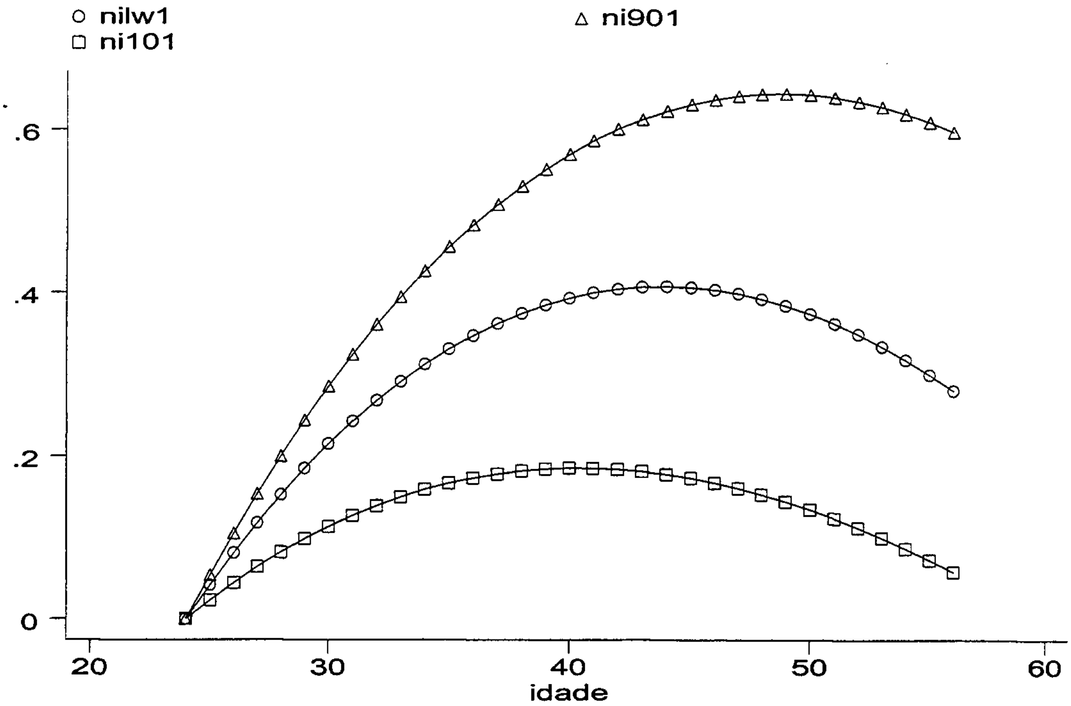
(13)


nilw772
nilw962
nilw872
1.6
1.4
1.2
1
.8
20
30
40
50
60
idade
returns to exp over time: educa2
stata™


nilw773
nilw873
nilw963
3
2.5
2
1.5
1
20
30
40
50
60
idade
returns to exp over time: educa3
stata

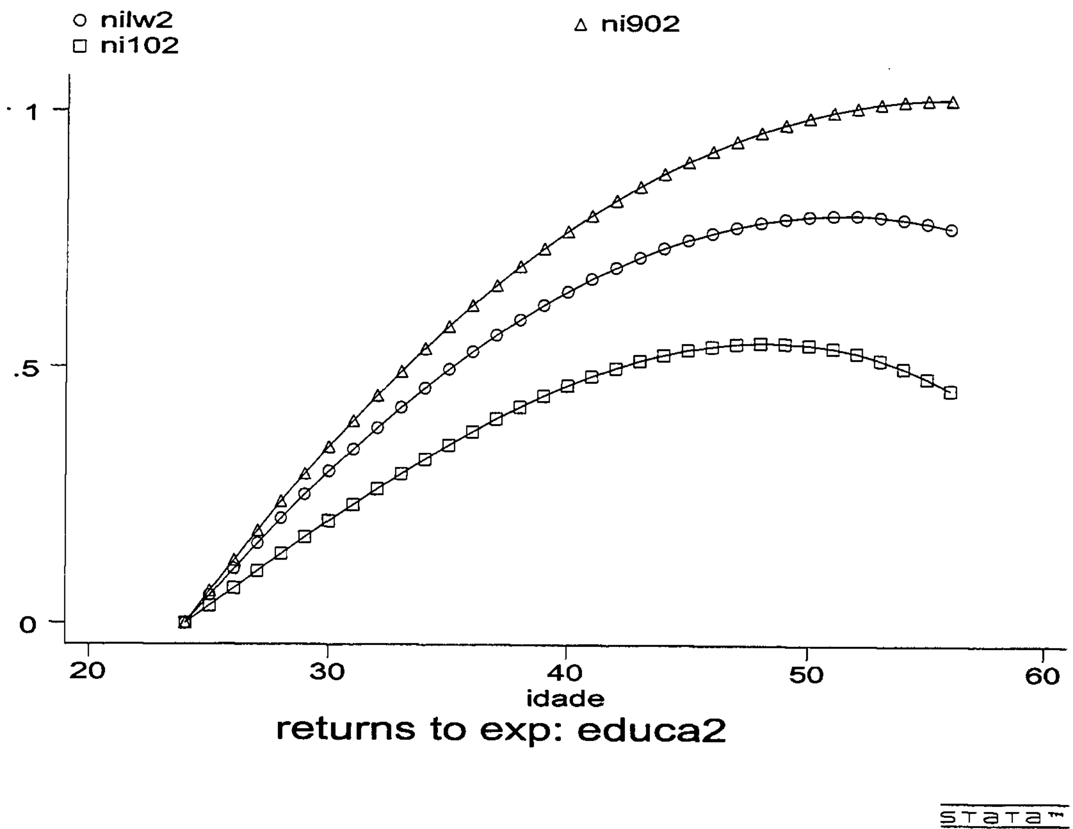


returns to exp over time: educa4

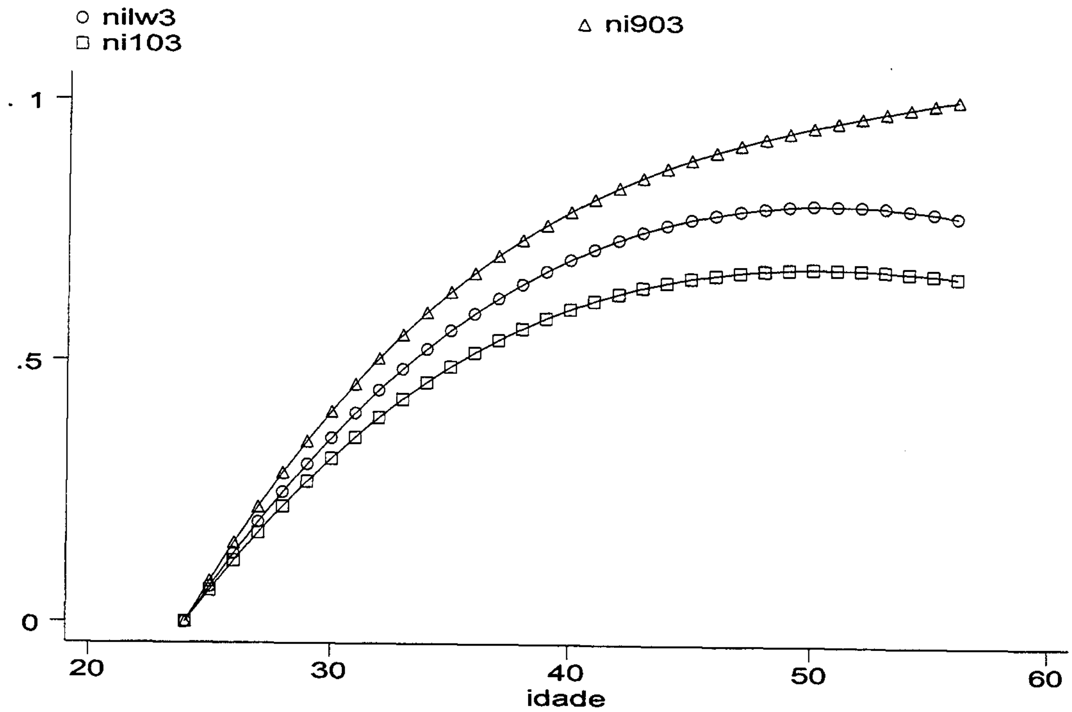


returns to exp: educa1

27

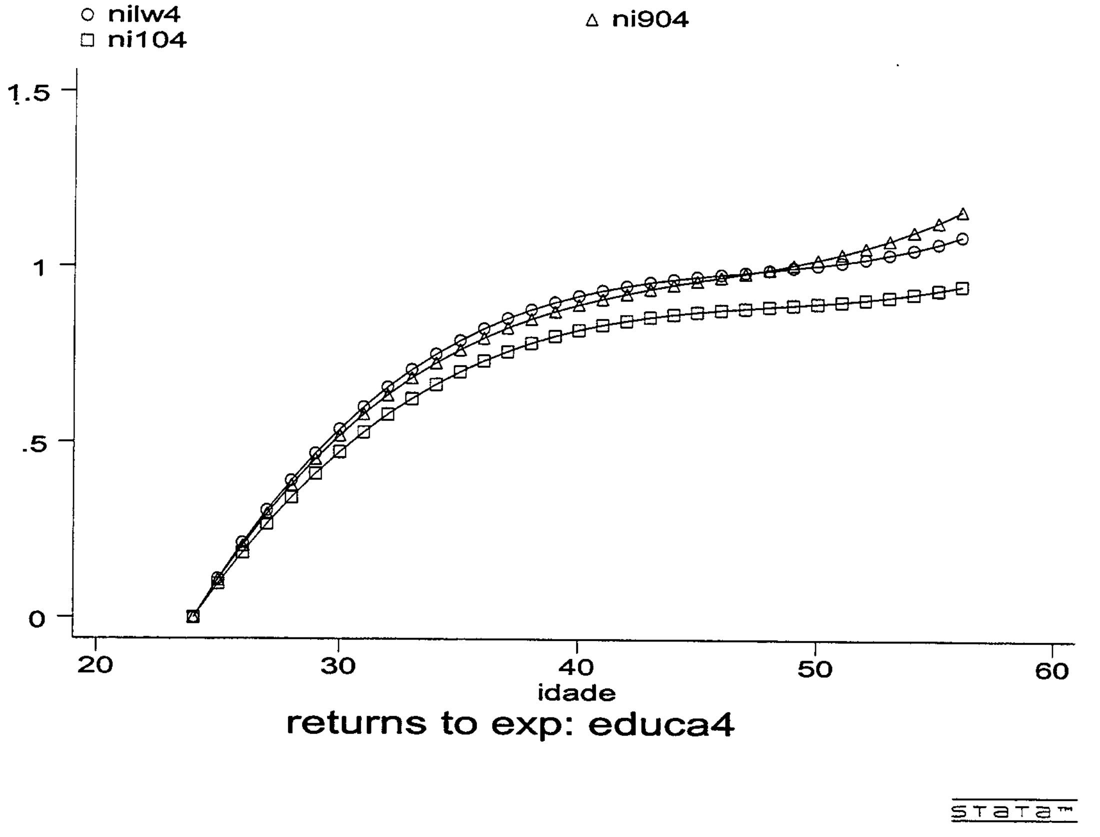

nilw2
ni102
ni902
1
.5
0
20
30
40
50
60
idade
returns to exp: educa2
STATA™

23

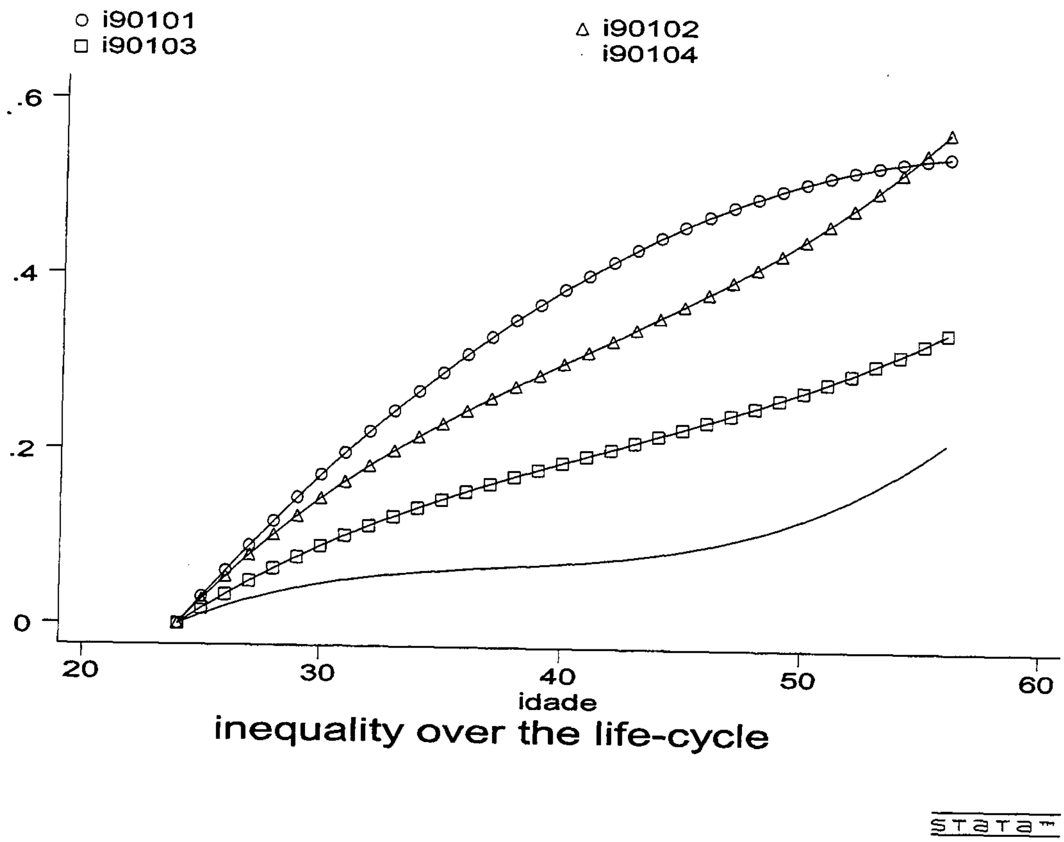


returns to exp: educa3

24



nilw4
ni104
ni904
1.5
1
.5
0
20
30
40
50
60
idade
returns to exp: educa4
stata™


i90101
i90103
i90102
i90104
.6
.4
.2
0
20
30
40
50
60
idade
inequality over the life-cycle
stata