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RANK AND QUANTITY MOBILITY IN THE EMPIRICAL DYNAMICS OF INEQUALITY

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Horizontal and vertical measures of inequality are related through mobility. The paper draws attention to two types of mobility: quantity mobility, which refers to mobility in income itself, and rank mobility, which refers to mobility in the position in the distribution of income. Individually matched census data for earnings in Israel are used to illustrate these concepts empirically. Mobility is measured between 1983 and 1995. It is shown that earnings in Israel are highly mobile. The high degree of earnings mobility implies that horizontal measures of inequality considerably overstate the underlying level of inequality. The method of errors in variables is used to distinguish between current and permanent mobility and inequality. Permanent earnings are more equal than current earnings and less mobile. Finally, the methodology is applied to PSID. It is shown that earnings were more mobile in Israel than in the United States.

1. Introduction

Longitudinal data on earnings and other types of income are becoming increasingly available, and there has been a corresponding growth in the empirical study of life-cycle or permanent inequality and economic mobility (e.g. Jarvis and Jenkins, 1998; Buchinsky and Hunt, 1999; Dickens, 2000; Haider, 2001). It has long been understood that due to economic mobility horizontal measures of inequality are likely to mislead and behave quite differently to longitudinal or vertical measures of inequality. Horizontal inequality may even increase, while longitudinal inequality decreases (Ben-Porath, 1967). Indeed, the empirical literature mentioned above[1] shows that horizontal measures of inequality considerably overstate underlying inequality due to mobility.

The data that I use in this paper for Israel add to the growing evidence that as a result of the high degree of economic mobility over the life-cycle, horizontal measures of inequality considerably overstate underlying inequality.[2] However, my main purpose is to elucidate the relationship between equality and mobility by introducing new measures of mobility, which distinguish between mobility in

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[1]See also Canto (2000) on seven-year mobility in Spain, Hauser and Fabig (1999) on one-year mobility in Germany, Smith (1994) on two-year mobility in the U.S., and Hungerford (1993) on seven-year mobility in the U.S.

[2]This finding supports Shayo and Vaknin (2000), who used a preliminary version of the data that I use, to show that there is substantial mobility into and out of poverty in Israel, and that the poor in 1983 and 1995 are largely different people. It also supports Romanov and Zusman (2000) who showed that there is a substantial degree of income mobility even over a relatively short time span of only three years.

quantity and mobility in rank. I show that mobility in quantity, which refers to relative changes in the quantity of income over time, is related to so-called beta convergence, or mean reversion. Mobility in rank occurs when the individual's position in the distribution changes without there necessarily being any change in the relative quantity of income. Indeed, it will be shown that upward mobility in quantity may coexist with downward mobility in rank.

The literature on inequality and mobility has been largely concerned with mobility in quantity. Since the concept of inequality is inextricably interwoven with rank, it seems natural to relate mobility in rank to the change in inequality. Indeed, I organize the discussion around various Gini measures of horizontal and longitudinal inequality, and Gini measures of mobility in rank and mobility in quantity. This provides an integrated approach, for investigating the interplay between horizontal and longitudinal inequality on the one hand, and mobility in rank and mobility in quantity on the other.

I use longitudinal earnings data for Israel measured at two points in time, 1983 and 1995, to measure earnings mobility, and longitudinal measures of inequality. The sample is large and does not suffer the usual problems of attrition and selectivity, despite the 12 year time span between the observations. Although more data points would have been desirable, what I have is of high quality and is sufficient to illustrate empirically the methodological agenda that has been proposed.

Apart from its methodological motivation, the paper also has a parochial motivation. As in the U.S. and U.K., but less so in Europe, wage inequality in Israel has been increasing both within and between educational groups and other groups. Dahan (2001) reports that the Gini for earnings rose from 0.255 in 1980 to 0.37 in 1995. Over a roughly similar period,[3] Gini for U.S. earnings rose from 0.323 to 0.366. Therefore, the increase in earnings inequality was much greater in Israel than in the U.S. These horizontal measures of inequality will overstate underlying inequality, especially if mobility is high. The results that I report show a surprisingly high degree of 12-year mobility, suggesting that horizontal measures of inequality considerably overstate underlying inequality in Israel.

2. Horizontal Inequality over Time

2.1. *The Israeli Labor Market*

Despite the fact that as many as 50 percent of workers are covered by collective wage agreements, the market for labor in Israel is deceptively flexible (Artstein, 2001), and is most probably among the most flexible of the industrialized countries. For example, the responsiveness of wages to unemployment is high by international standards (Beenstock and Ribon, 1993; Yashiv, 2000), and the labor market has absorbed several waves of mass immigration without appreciably affecting the rate of unemployment (Beenstock and Fisher, 1997). During the 1990s the population of working age rose by more than 20 percent, but the rate of unemployment scarcely rose in the medium term. Moreover, the economy also

[3]See Section 6.

absorbed a large number of foreign workers, who in 2002 accounted for almost 11 percent of employment, roughly half of whom were in Israel illegally (Amir, 2002).

Following the Six Day War in 1967 Palestinian workers began to work inside Israel (Angrist, 1996). Before the outbreak of the first Intifada in 1988, they accounted for almost 7 percent of employment. However, by 2002 this proportion fell to 1.2 percent. The arithmetic implies that not only did non-Palestinian foreign workers replace Palestinian workers, but the proportion of foreign workers grew by 4 percentage points during the 1990s. Another distinctive feature of Israel's labor market is the relation between the Jewish and Arab sectors of the market, where the latter are relatively unskilled (10.2 years' education in 2000) and accounted for 13.6 percent of employment in 2000, and the former are skilled (12.8 years' education).

The unusual degree of flexibility of the labor market may be partly attributed to the fact that despite the pervasiveness of collective wage agreements there is a surprisingly high degree of local flexibility in wage setting. Also, competition from foreign workers, Arab workers and immigrants has most probably increased the flexibility of the labor market. Another factor that has encouraged flexibility is the unemployment benefit system, which provides benefit for a limited period of six months. In this Israel follows the U.S. model rather than the European model.

If flexibility and mobility are complementary, the flexibility of the Israeli labor market is likely to find expression in greater wage mobility. Indeed, the evidence on mobility cited below further testifies to the flexibility of the market for labor in Israel.

2.2. *The Data*

Israel's Central Bureau of Statistics (CBS) has used personal ID information to match the censuses of 1983 and 1995. In what follows we refer to this as the Matched Census Data (MCD). The census questionnaire has two parts. Part A is completed by 100 percent of the population, and provides basic demographic information. Part B, which is completed by a random sample of 20 percent of the population, provides data on income by source and a variety of other variables. Part B of MCD therefore provides an opportunity to investigate income mobility between 1983 and 1995. Moreover, because MCD uses census data, the usual problems of sample attrition that arise in survey data (such as PSID and NYLS) do not apply. The probability of an individual featuring in part B of MCD in both 1983 and 1995 is 0.04 (20 percent of 20 percent), because only 20 percent of those featuring in part B in 1983 will be sampled in part B in 1995. In practice the probability is slightly smaller than this due to death and emigration between 1983 and 1995. This still leaves us with a large random sample.

The data have some obvious shortcomings. There are only two data points, 1983 and 1995. Rival data sets, such as PSID and NYLS, have many data points, which enables the longitudinal investigation of different cohorts, and the calculation of permanent or longitudinal income averages for each individual. Therefore I cannot apply the accounting period analysis used by Buchinsky and Hunt (1999), Dickens (2000) and Haider (2001). On the other hand, the sample size in MCD is much greater and, as mentioned, MCD is unusual in that unlike PSID and NYLS

TABLE 1
ORDERED LOGIT MODEL FOR EMPLOYABILITY

	Odds Ratio	p-value
Intercept 1	1.3074	<0.0001
Intercept 2	–0.6492	<0.0001
Male	0.744	<0.0001
Age	1.120	<0.0001
Age^2	0.998	<0.0001
Higher education	1.261	<0.0001
Matriculation	1.078	0.0946
Student	0.840	0.0297
Eastern Europe	1.126	0.0031

there is no sample attrition. This is particularly useful when long-term mobility (12 years) is being investigated.

Self-reported gross wage data in MCD refer to April 1983[4] and September 1995, i.e. the data are monthly in both cases. This is important because Gini tends to vary inversely with the number and length of accounting periods (Shorrocks, 1978). The data refer to salaried workers; hence the self-employed, who in 1995 constituted about 6.5 percent of the labor force, are excluded.[5] The observations in the "study group" are restricted to 20,454 people, who participated in the labor market in both 1983 and 1995, and who were aged between 25 and 50 in 1983; henceforth the "participants." The latter restriction is made so that they should not be too old in 1995 nor too young in 1983. Five percent of this study group were unemployed in both 1983 and 1995, and 73 percent were employed in both time periods. The number of people in the study group reporting positive earnings in both 1983 and 1995 is 15,366; henceforth the "earners."

An ordered logit model, reported in Table 1, indicates the observed characteristics that are significantly associated with "employability" (0 = unemployed in 1983 and 1995, 1 = unemployed in 1983 or 1995, 2 = employed in 1983 and 1995). Table 1 indicates that "employability" is higher for women, varies directly with education, and has a ∩-shaped relationship with age. It also tends to be higher among people of Eastern European origin. Individuals who were unemployed have zero earnings. Individuals who did not participate in either or both of 1983 and 1995 are excluded from the study group.[6]

2.3. *Horizontal Inequality in 1983 and 1995*

The Gini coefficient for gross earnings in 1983 for the study group (Table 2, section 1) was 0.501 and in 1995 it was 0.461, implying that inequality within the study group slightly decreased between 1983 and 1995. The Gini coefficient for the

[4]In the 1983 Census, data are also supplied for February and March, but have not been included by CBS.

[5]Because the earnings data for the self-employed are unreliable.

[6]The alternative is to assume that non-participation means that earnings are zero. The Gini including these observations is equal to $(1 - p) + pG$ where $1 - p$ is the proportion of observations with zero earnings. This was first shown by Gavish and Yitzhaki (1988).

TABLE 2

COMPARATIVE GINI COEFFICIENTS FOR GROSS EARNINGS

	1983		1995	
	Participants	Earners	Participants	Earners
1. Study group	0.501	0.381	0.461	0.391
	(20,454)	(15,366)	(20,454)	(15,366)
2. Census				
Aged 25–50 in 1983	0.541	0.391	0.481	0.412
	(172,872)	(130,255)	(150,648)	(132,966)
Aged >15 in 1983	0.570	0.413	0.476	0.403
	(273,694)	(200,565)	(236,563)	(207,652)
Aged >15 in 1995			0.483	0.409
			(318,076)	(278,360)
3. MCD				
Aged >15 in 1983	0.553	0.411	0.483	0.414
	(42,407)	(32,171)	(38,966)	(34,364)
Aged >15 in 1995			0.493	0.425
			(52,898)	(46,595)
Aged 25–50 in 1983	0.527	0.387	0.485	0.420
	(28,050)	(21,674)	(25,092)	(22,243)
4. Household Income Survey				
Aged 25–50 in 1983	0.372	0.341	0.447	0.410
	(3,667)	(3,491)	(3,752)	(3,518)
Aged >15 in 1983	0.412	0.368	0.444	0.402
	(5,995)	(5,584)	(6,199)	(5,763)
Aged >15 in 1995			0.471	0.417
			(8,326)	(7,555)
5. National Insurance Institute[a]	0.439		0.497	

Notes:
[a]Economic income.
Number of observations in parentheses.

employed in the study group (excluding individuals who were unemployed in either or both of 1983 and 1995) marginally increased from 0.381 to 0.391. Note that because the sample size is large, changes in Gini greater than 0.0015 are statistically significant at $p = 0.05$.[7] To judge the scale of these changes in inequality, they may be compared with the change in Gini for U.S. earnings over a similar period.[8] The Gini for participants rose from 0.367 in 1980 to 0.422 in 1992, and the Gini for earners rose from 0.323 to 0.366.

For purposes of comparison, Table 2 reports Gini coefficients for gross earnings derived from different sources. We begin (section 2) by using the Census data to calculate Gini for the age groups in the study group (25–50 in 1983). This confirms that whereas for participants in the labor market Gini decreased between 1983 and 1995, it increased among earners. However, the census Ginis tend to differ slightly from their study group counterparts, especially in 1983 for participants. Section 2 of Table 2 also reports Ginis for broader age groups. This shows

[7]Using the jack-knife methodology proposed by Yitzhaki (1991).
[8]See Section 6.

that according to the censuses Gini did not increase between 1983 and 1995, and even decreased slightly.

Section 3 of Table 2 uses MCD to calculate Ginis for different age groups without restricting the data to panel observations. Hence, the sample size varies in each calculation, and exceeds its counterpart in section 1 even for individuals aged 20–50 in 1983, implying less inequality among the study group than the population as a whole. The Ginis for the study group fall slightly below their counterparts in section 3.

The calculations reported in sections 1–3 of Table 2 are based on a common data source, namely the Censuses for 1983 and 1995. An independent data source of the Central Bureau of Statistics is HIS (Household Income Survey), which in 1983 referred to annual income and in 1995 referred to quarterly income. This change in the accounting period would tend to raise measured inequality in 1995 relative to 1983 even if there had been no change the distribution of income. Like the census data, HIS data are self-reported. In section 4 of Table 2, I use earnings data from HIS to calculate Gini in 1983 and 1995. It shows that Gini increased, and contradicts the findings in the census data.[9] Although we cannot determine to what extent the increase in Gini is induced by the shortening of the accounting period, the scale of the increase implies that horizontal inequality in earnings was greater in 1995 than in 1983.

Another independent source of data is the National Insurance Institute (NII). Section 5 of Table 2 shows that according to NII wage inequality increased between 1983 and 1995.

In summary, it is disconcerting but salutary to note that different data sources imply different trends in inequality. The census data show that earnings inequality did not increase between 1983 and 1995, and even decreased slightly. In contrast HIS and NII data indicate that horizontal inequality increased.

3. Measuring Mobility

3.1. *Longitudinal Inequality*

Shorrocks (1978) proposed that the Gini for average income during the accounting period ($\tilde{G}$) be compared to the average of the individual horizontal Ginis in the accounting period ($\overline{G}$). The Shorrocks index of immobility is defined as $s = \tilde{G}/\overline{G}$. There is no mobility when $s = 1$, the degree of mobility varies inversely with s, and s typically varies inversely with the length and number of accounting periods.

I refer to $\tilde{G}$ as the longitudinal Gini coefficient. In our case longitudinal Gini is calculated using average earnings in 1983 and 1995 (at constant prices), which is compared to the average of the horizontal Ginis for 1983 and 1995. In MCD the average horizontal Gini for 1983 and 1995 is 0.481, and longitudinal Gini is 0.416, which suggests a considerable degree of mobility. Note that longitudinal

[9] Dahan (2001) also uses HIS. He reports that Gini for full-time earnings of males aged 25–65 rose from 0.324 in 1983 to 0.37 in 1995.

Gini varies inversely both with the length of the accounting period and the number of periods. Had I been able to average income over all 12 years instead of just two, longitudinal Gini would have been even lower than 0.416, and the implied degree of mobility would have been even greater, under the reasonable assumption that mobility occurred in the intervening years.

3.2. *Rank Mobility and Quantity Mobility*

Shorrocks mobility conceals two quite distinct phenomena. The first is concerned with regression to the mean, or beta convergence, according to which the incomes of those earning below the average in 1983 tend to rise towards the mean, while the incomes of those earning above the average in 1983 tend to fall towards the mean. I refer to this kind of mobility as "quantity mobility" because it is concerned with the change in the quantity of income in either absolute or percentage terms. The second phenomenon refers to the rank of the individual in the income distribution. If his rank rises over time he is upwardly mobile, and if it falls he is downwardly mobile. I refer to this as "rank mobility."

Rank and quantity mobility are quite different phenomena. An individual's rank in the distribution may change without his income changing in relative terms and vice-versa. The relationship between the two measures of mobility has been clarified by Wodon and Yitzhaki (2001). In what follows Y_{it} denotes the income of individual $i = 1, 2, \ldots, N$ in period $t = 1, 2$ and R_{it} denotes the rank out of N in the respective income distribution. The mean reversion model is:

$$Y_{i2} = \alpha + \beta Y_{i1} + \varepsilon_{i2} \tag{1}$$

where ε is a random error term. If $0 < \beta < 1$ there is "beta convergence" or mean reversion in Y; there is downward quantity mobility in Y among the better off, and upward quantity mobility among the worse off. If $\beta > 1$ there is mean diversion in Y. β may be estimated in a variety of different ways including OLS and IV. An alternative is to estimate β from a Gini regression (Olkin and Yitzhaki, 1992) in which Y_2 is regressed on R_1 rather than Y_1. This Gini regression estimate is denoted by β^*. It may be regarded as a semiparametric estimate of β because the rank (R) is independent of how Y is measured, such as in levels or logarithms. Alternatively, β^* may be regarded as an IV estimate in which Y_1 is instrumented by R_1. Since there is presumably less measurement error in R than Y, β^* is likely to be subject to less bias than its OLS counterpart.

Wodon and Yitzhaki (2001) show that β^* may be expressed as:

$$\beta^* = \frac{\mathrm{cov}(Y_2 R_1)}{\mathrm{cov}(Y_1 R_1)} = \Gamma_{21} \frac{G_2}{G_1} \frac{\overline{Y_2}}{\overline{Y_1}} \tag{2}$$

where G_t denotes Gini in time period t and:

$$\Gamma_{21} = \frac{\mathrm{cov}(Y_2, R_1)}{\mathrm{cov}(Y_2, R_2)} \tag{3}$$

denotes the backward Gini correlation coefficient (Schechtman and Yitzhaki, 1987), which is bounded between 1 when there is no rank mobility, i.e. when $R_1 =$

R_2, and −1, when $R_1 = N - R_2$. If R_1 and R_2 are independent then $\Gamma_{21} = 0$. Unlike Spearman's correlation coefficient the Gini correlation is not sensitive to arbitrary scaling of Y, and unlike Pearson's rank correlation coefficient it gives expression to the degree of quantity mobility. However, it is sensitive to the choice of base period so that the forward Gini correlation Γ_{12} does not generally equal its backward counterpart Γ_{21}, unless Y_1 and Y_2 happen to be exchangeable. Exchangeability means that the shapes of the marginal distributions of Y_1 and Y_2 are similar. If the data are exchangeable, the base period does not matter for calculating Γ. In our data it turns out that the data are not exchangeable, which means that backward and forward measures of quantity mobility differ. The implications of this are discussed in Section 3.3.

Equation (2) states that β^*, which measures the degree of quantity immobility, varies proportionately with Γ_{21}, which measures the degree of rank immobility. It also varies directly with the degree of Gini convergence, and leveling-up (growth) as measured by the mean of income in period 2 relative to its counterpart in period 1. In the absence of Gini convergence or divergence and leveling effects, quantity and rank mobility are identical since according to Equation (2) $\beta^* = \Gamma_{21}$, but in general they differ and vary independently of each other. Indeed, quantity and rank mobility may change in opposite directions. This will happen, for example, when the percentage increase in Γ_{21} happens to be smaller than the percentage decrease in mean preserving Gini convergence (G_2/G_1). Equation (2) further establishes that there is no necessary connection between beta convergence and Gini convergence.

Inequality may be measured by the standard deviation of Y (σ_Y) instead of Gini. Sigma convergence (divergence) occurs when σ_Y falls (rises) over time. If β is estimated by OLS it may be shown[10] that beta and sigma convergence are related as follows:

$$\beta_{\text{OLS}} = r\frac{\sigma_{Y2}}{\sigma_{Y1}} \tag{4}$$

where r is the correlation coefficient between Y_1 and Y_2. Equation (4) states that sigma convergence necessarily implies beta convergence because both r and σ_{Y2}/σ_{Y1} are less than unity. However, the converse is not true; beta convergence does not necessarily imply sigma convergence, since β_{OLS} can be less than unity despite the fact that $\sigma_{Y2} > \sigma_{Y1}$. Another obvious difference between the Gini and least squares frameworks is that the latter only measures quantity mobility, and does not distinguish between quantity and rank mobility.

In Table 3, Equation (2) is used to decompose β^* and to distinguish between rank and quantity mobility. The Gini correlation coefficient for participants in 1983 and 1995 is 0.4405, and the estimate of β from a Gini regression is 0.4932. The disparity between the two mobility measures reflects the leveling-up of earnings by 21.55 percent between 1983 and 1995, which was partially offset by Gini convergence between 1983 and 1995. In the absence of Gini convergence the gap between the two measures of mobility would have been greater, and in the absence

[10]This was originally shown by Mulligan (1997, p. 168), but see also Wodon and Yitzhaki (2001).

TABLE 3

DECOMPOSING BETA

	N	Γ_{21}	G_2/G_1	Y_2/Y_1	β^* (Gini)	β (OLS)
Current	20,454	0.4405	0.921	1.2155	0.4932	0.3147
Permanent	16,276	0.7790	1.148	1.1800	1.0550	1.0420

Notes: The data used refer to individuals aged 25–52 in 1983 with earnings in 1983 and 1995.

of leveling-up the gap would have been smaller. The second row in Table 3 is discussed in Section 4.3.

Table 3 also reports the OLS estimate of β, which turns out to be smaller than its Gini counterpart, which, as mentioned, suggests that the OLS estimate is biased downward due to measurement error. Since $r = 0.3161$ and $r > \beta_{\text{OLS}} = 0.3147$, Equation (4) implies that sigma slightly diverged between 1983 and 1995.

3.3. *Gini Mobility Index*

In Section 3.2 it was noted that, in the absence of exchangeability, forward and backward measures of mobility are generally different, i.e. $\Gamma_{21} \neq \Gamma_{12}$. Indeed, it turns out that our data are not exchangeable. Yitzhaki and Wodon (2000) have proposed a symmetric index of rank mobility, which measures the degree to which income ranks vary between the two time periods by weighting forward and backward measures of mobility. It is defined as:

$$S = \frac{(1-\Gamma_{12})G_1 + (1-\Gamma_{21})G_2}{G_1 + G_2} \tag{5}$$

If Y is exchangeable $\Gamma_{21} = \Gamma_{12} = \Gamma$, and Equation (5) simplifies to $S = 1 - \Gamma$. If the ranks do not change, there is no mobility, and $S = 0$. If there is no correlation between income rank in the two periods, i.e. mobility is random, $\Gamma = 0$ and $S = 1$. For all practical purposes this is the case of complete mobility because it means that income rank in period 2 cannot be predicted from income rank in period 1. If, however, there is reverse mobility in which those with above average rank systematically change places with those below average rank then $S > 1$. If mobility is perfectly reverse, i.e. top ranked changes place with the bottom ranked, and so on, then $\Gamma = -1$ and $S = 2$.

There is a widespread practice in the empirical literature on mobility to compute mobility matrices by percentiles, typically deciles. There is zero mobility if the mobility matrix is diagonal. The degree of mobility increases the more non-diagonal the matrix. The Gini mobility index is superior in a number of respects. Firstly, it is sensitive to mobility within deciles and does not depend upon arbitrary definitions of percentiles. Secondly, apart from giving weight to immobility along the diagonal, it also gives weight to the extent of mobility off the diagonal. Finally, it does not depend upon arbitrary scaling of income, e.g. logarithmic scaling. It is obvious that if there is no mobility between deciles the mobility matrix approach will create the misleading impression of complete immobility, when in fact there might be substantial mobility within deciles. If the percentiles are refined the mobility matrix approach will begin to reveal mobility that was previously

TABLE 4
Gini Mobility Indices

Group	N	S
All	21,338	0.554
Non-Jews	1,936	0.641
Jews	19,402	0.558
Men	13,103	0.578
Women	8,235	0.565
Jewish women: higher education	4,463	0.649
Jewish women: matriculation	1,300	0.617
Jewish women: no matriculation	3,372	0.614
Jewish men: higher education	4,756	0.665
Jewish men: matriculation	6,293	0.636

concealed. Essentially, the Gini mobility index refines the percentiles down to the finest level, namely the individual. This is why it is more general. If, however, intra-percentile mobility is of no interest mobility matrices will continue to be useful.

The Gini mobility index sheds important new light on the index of mobility suggested by Shorrocks (s) mentioned in Section 2.1. The relationship between s and S may be illustrated as follows assuming for simplicity that the accounting period is of length 2 and that Y is exchangeable. The Gini coefficient for average income is related to the horizontal Ginis as follows:[11]

$$\tilde{G}^2 = \frac{1}{4}(G_1^2 + G_2^2 + 2\Gamma G_1 G_2) \tag{6}$$

If $\Gamma = 1$ there is no mobility, and Equation (6) states that the Gini for average income is equal to the average of the Gini coefficients, i.e. $\tilde{G} = \overline{G}$. If $\Gamma = 0$, i.e. there is random mobility, Equation (6) states that $\tilde{G} = 0.7071\overline{G}$ in which case $s =$ 0.7071. Finally, if $\Gamma = -1$, i.e. there is perfect reverse mobility, Equation (6) states that $\tilde{G} = 0$, i.e. mean income is perfectly equal regardless of $\overline{G}$ in which case $s =$ 0. In short, Shorrocks' index can be expressed in terms of the Gini mobility index.

The Gini Mobility Index (S) for the study group as a whole is 0.554 (Table 4) for earners and 0.421 for participants, which implies perhaps a surprisingly high degree of mobility. Indeed, this mobility may be seen in Figures 1 (for those earning in 1983 and 1995) and 2 (for labor market participants), which plots earnings rank in 1983 against the rank in 1995. Had all the observations fallen on an (imaginary) 45° line emanating from the origin there would have been no mobility ($S = 0$). However, the majority of the observations fall either below this line (upward mobility) or above it (downward mobility). Note, however, that the data cloud tends to thicken at the top and bottom ends of the 45° line, implying that mobility diminishes at the top and bottom ends of the earnings distribution.

[11]Average income is $\frac{1}{2}(Y_1 + Y_2)$. Equation (6) has the same quadratic form as the variance, which is $\frac{1}{4}(\sigma_1^2 + \sigma_2^2 + 2r\sigma_1\sigma_2)$, hence G replaces σ and Γ replaces r.

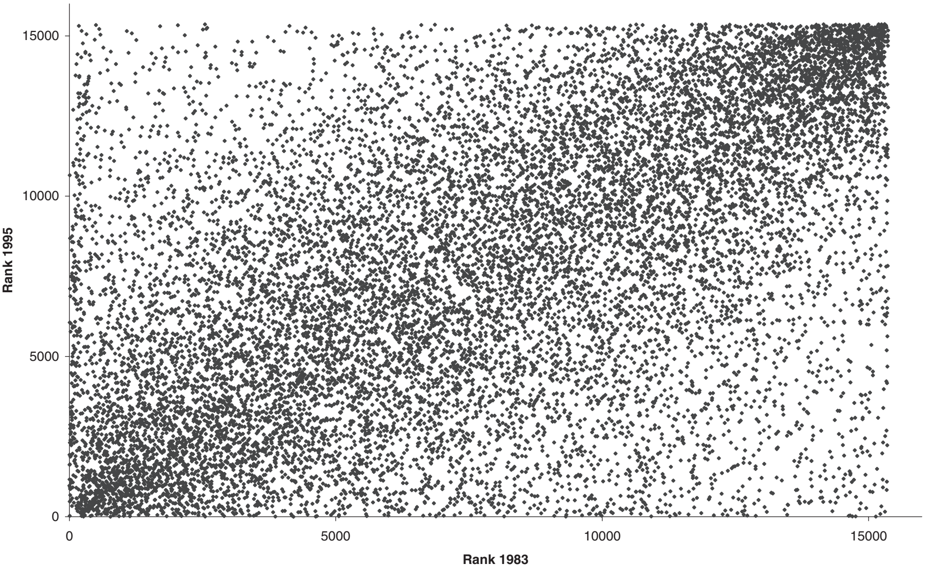

Figure 1. Earnings Mobility–Employed

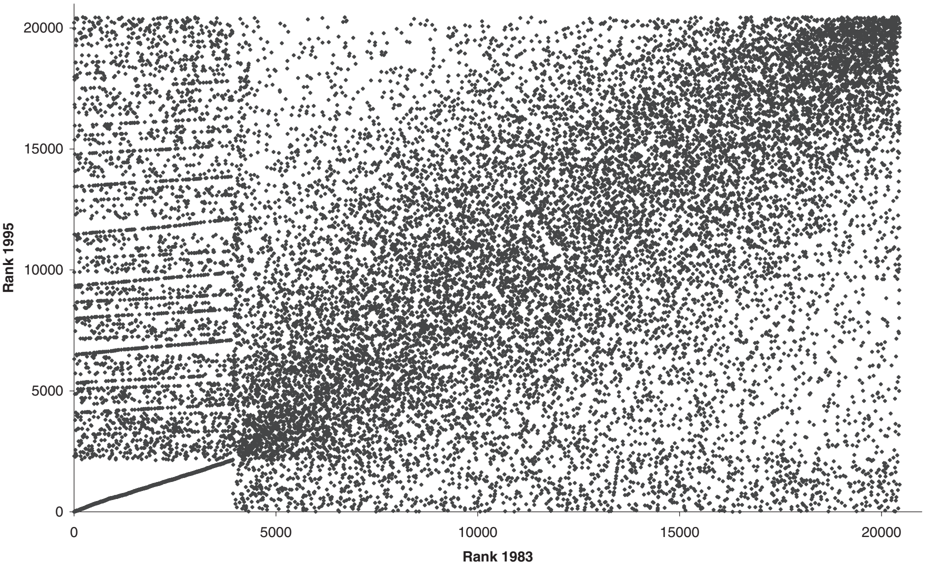

Figure 2. Earnings Mobility–Employed

Table 4 reports Gini Mobility Indices for a variety of subgroups. Non-Jews are considerably more mobile within their group than their Jewish counterparts. The most mobile group comprises Jewish men with higher education ($S = 0.665$). However, Jewish women with higher education do not lag far behind ($S = 0.649$). Indeed, within group mobility is generally similar for men and women. Also, within group mobility varies directly with education, implying that the relationship between earnings and age is steeper for the more educated. Because the sample sizes are large, even small differences between S for different groups are statistically significant (see footnote 7). Since S has the same dimensionality of a correlation coefficient the difference between a value of S for non-Jews (0.641) and Jews (0.558) should be regarded in the same way that one would regard the difference between two correlation coefficients.

Note that the mobility index for the population as a whole is smaller than its group counterparts. The population S may be larger or smaller than its sub-group counterparts. For example, if mobility within the groups is zero, but the ranks of mean group income happen to change, then the population S will be positive despite the fact that S for the sub-groups is zero. By reverse reasoning the population S may be less than the smallest S of the sub-groups, as in Table 4.

3.4. *Correlates of Mobility*

To determine the correlates of mobility, the change in (global) rank between 1983 and 1995 was regressed on a broad range of demographic variables, many of which were not statistically significant. Model 1 in Table 5 retains the variables that turned out to be statistically significant. It shows that upward mobility increases with educational status (as of 1983). For example, individuals with higher education rose on average by 525 places out of 20,015 between 1983 and 1995. Jews were also slightly more upwardly mobile than non-Jews, as were second generation people of Eastern European origin. The 3rd order polynomial in age (in 1983) implies that upward mobility varies inversely with age except for people aged about 40.

Model 2 in Table 5 defines the regressand as the rank in 1995 and includes the rank in 1983 as a regressor. Not surprisingly, the latter is statistically significant, however, the coefficient is quite small, which is consistent with the high degree of income mobility that has already been noted. Had this coefficient been zero, the conditional effect of income rank in 1983 would have had no predictive power regarding rank in 1995. Model 2 also includes some demographic variables that were not statistically significant in model 1. Note, however, that model 2 implies that the long run level of the rank, as well as its change, depends upon these variables. For example, the coefficient on "urban" implies that on average the urban population improved its rank by 267 places between 1983 and 1995. In the long run the rank of this group tends to be 415 places higher (267/(1 – 0.3562)).

4. Data Problems and Related Adjustments

The discussion so far has focused on the raw data, as used in conventional measures of horizontal inequality. The literature has drawn attention to why the raw data may misrepresent the underlying degree of inequality and mobility. In this section I address some of these issues and discuss their implica-

TABLE 5

MOBILITY REGRESSIONS

	Model 1: Mobility		Model 2: Rank 1995	
	Coefficient	p-value	Coefficient	p-value
Intercept	25,567	0.0004	115.92	0.9133
Student	3,515	0.0001	3,421.8	0.0001
Higher education	525.14	0.0001	2,384.6	0.0001
Matriculation	427.85	0.0057	1,423.4	0.0001
Age	–2,035.56	0.0009	177.48	0.0029
Age^2	52.90	0.0017	–3.032	0.0002
Age^3	–0.4684	0.0022		
Jewish	480.25	0.0042	1,792.0	0.0001
Eastern Europe 2	506.74	0.0001	942.94	0.0038
Western Europe 2			537.71	0.0018
Eastern Europe 1			323.78	0.0038
Urban			267.15	0.0016
Sex			1,791.2	0.0001
Rank 1983			0.3562	0.0001
R^2 adj	0.0179		0.2559	

Notes: N = 20,015. Origin 1 and 2 denote first and second generations respectively.

tions for the measurements of mobility and inequality that have been thus far presented.

4.1. *Life-Cycle Issues*

As noted by Paglin (1975) some mobility happens naturally over the life-cycle. The earnings of the young tend to increase, whereas the earnings of older workers tend to decrease. To neutralize the effect of aging on S the data are age-adjusted by estimating Equation (7):

$$Y_{it} = \alpha_t + \sum_{1}^{K_t} \theta_{kt} A_{it}^k + u_{it} \tag{7}$$

where $t = 1$, 2, and A denotes age. Note that the order of the polynomial in age may vary in the two time periods, since the relationship between earnings and age may vary over time. Solon (1992) and Mulligan (1997) among many others specify a polynomial in age. An alternative would have been to estimate this relationship non-parametrically by allowing a different coefficient for each age group. Age-adjusted earnings are defined as:

$$\tilde{Y}_{it} = \hat{\alpha}_t + \hat{u}_{it} \tag{8}$$

where $\wedge$ denotes an OLS estimate. Equation (7) confounds age effects and birth cohort effects, because individuals who were older in 1983 were born earlier. Ideally, it would have been desirable to estimate separate cohort and age effects as, for example, Dickens (2000). However, this requires more than two panel observations, and is therefore unfeasible here. The age-adjusted earnings data are then used to calculated age-adjusted indices of earnings mobility, as well as age-adjusted Gini coefficients. The latter is a horizontal measure of inequality in which the data have been adjusted for life-cycle (age) effects.

TABLE 6

AGE-ADJUSTMENT COEFFICIENTS

	1983	1995
α	−39,308 (0.0001)	389,190 (0.0491)
β_1	32,19.9 (0.0001)	−56,340 (0.0443)
β_2	−35.4 (0.0001)	3,227 (0.0394)
β_3	0	−90.4 (0.0366)
β_4	0	1.2426 (0.0351)
β_5	0	−0.0067 (0.0345)

Note: P-values in parentheses.

Table 6 reports estimates of Equation (7) for 1983 and 1995. In the former case a 2nd order polynomial sufficed ($K = 2$), while in the latter a 5th order polynomial turned out to be statistically significant ($K = 5$). The implied age-adjusted Ginis are reported in Table 7. For example, in the case of participants Gini in 1983 is equal to 0.479 instead of 0.501, and S increases to 0.586 from 0.554. Age-adjusting tends to reduce Gini and increase Gini mobility. Age-adjusted Gini is naturally smaller than its raw counterpart because some of the raw inequality is incurred by inequality in age. Age-adjusted Gini mobility may be greater or smaller than its raw counterpart as may be demonstrated as follows. If for simplicity $K = 1$ in Equation (7), then Equation (3) becomes:

$$\Gamma_{21} = \frac{\theta \operatorname{cov}(A_2, R_{A1}) + \operatorname{cov}(u_2, R_{u1})}{\theta \operatorname{cov}(A_2, R_{A2}) + \operatorname{cov}(u_{u2}, R_{u2})}$$

where R_A denotes the rank of age and R_u denotes the rank of u. Since $R_{A1} = R_{A2}$ $\operatorname{cov}(A_2, R_{A2}) = \operatorname{cov}(A_2, R_{A1})$. Dividing top and bottom by $\operatorname{cov}(u_2, R_{u2})$ and rearranging yields:

$$\Gamma_{u21} = \Gamma_{21} + \kappa(\Gamma_{21} - 1)$$

$$\kappa = \theta \frac{\operatorname{cov}(A_2, R_{A2})}{\operatorname{cov}(u_2, R_{u2})}$$

$$\Gamma_{21} = \frac{\operatorname{cov}(u_2, R_{u1})}{\operatorname{cov}(u_2, R_{u2})}$$

which implies that the age-adjusted Gini correlation (Γ_u) is smaller and mobility correspondingly greater than its raw counterpart when $\theta > 0$. The opposite applies if $\theta < 0$.

4.2. *Permanent Inequality and Mobility*

It is either assumed that the data are measured with error, or that current earnings, as reported, differ from permanent earnings (Y^*). Hence:

$$Y_{it} = Y^*_{it} + e_{it} \tag{9}$$

where e denotes measurement error and/or transitory earnings, and is assumed to have some unknown distribution. Using Equation (9) we may distinguish between the rank of current earnings and the rank of permanent earnings, $R^* = F(Y^*)$. Hence:

(10) $$R_{it} = R_{it}^{*} + v_{it}.$$

Once e is known or estimated, v is determined via Equation (10), and $\mathrm{cov}(ev) > 0$. We may then calculate Gini for permanent earnings (G^*), following Shechtman and Yitzhaki (1987), as:

(11) $$G^* = \frac{2\,\mathrm{cov}(Y^*\,R^*)}{\bar{Y}^*} = G - 2\frac{\mathrm{cov}(vY) + \mathrm{cov}(eR) - \mathrm{cov}(ev)}{\bar{Y}^*}$$

In Equation (11) it is assumed for convenience that $E(e) = 0$. Equation (11) states that permanent Gini will be smaller than current Gini when $\mathrm{cov}(vY) + \mathrm{cov}(eR) > \mathrm{cov}(ev)$.

The permanent Gini correlation is obtained by substituting Y^* and R^* into Equation (3). For example, the forward permanent Gini correlation is:

(12) $$\Gamma_{12}^{*} = \frac{\mathrm{cov}(Y_1^*\ R_2^*)}{\mathrm{cov}(Y_1^*\ R_1^*)} = \frac{\Gamma_{12} - \dfrac{\mathrm{cov}(Y_1 v_2) + \mathrm{cov}(e_1 R_2^*)}{\mathrm{cov}(Y_1 R_1)}}{1 - \dfrac{\mathrm{cov}(Y_1 v_1) + \mathrm{cov}(e_1 R_1^*)}{\mathrm{cov}(Y_1 R_1)}}$$

Equation (12) also reveals the relationship between the permanent and current Gini correlation. They are the same ($\Gamma^* = \Gamma$) when $\mathrm{cov}(Y_1 v_2) + \mathrm{cov}(e_1 R_2^*) = \mathrm{cov}(Y_1 v_1) + \mathrm{cov}(e_1 R_1^*) = 0$. This will happen when transitory rank (v) is independent of income and when transitory income (e) is independent of permanent rank. Finally, the permanent Gini mobility index (S^*) is calculated by substituting permanent measures of the parameters into Equation (5). Since some of the measured mobility is inherently transitory, we may expect S^* to be smaller than S.

Since MCD contains only two data points per individual it is not possible to represent permanent earnings by taking a moving average of earnings, as do, for example, Buchinsky and Hunt (1999) and Haider (2001). Also, as mentioned in Section 4.1, the availability of but two data points prevents us from distinguishing different birth cohorts. Instead, we follow Solon (1992) who in a similar context used the method of errors in variables to estimate permanent earnings. This method was applied to estimate Y^* in 1983 and in 1995. Two separate but related issues are involved here. Firstly, it is better to use earnings averaged over a number of years than earnings in a single year. Secondly, there may be measurement errors in either or both of single year earnings and averaged earnings. While it obviously would have been better had MCD contained more data points than two, I try to overcome the shortcomings of MCD by distinguishing between types of instrument. One set of instruments is specified to capture measurement error, while another set is specified to capture the permanent component of earnings.

To gain some insight into the contributions of instrumentation and data averaging, Mulligan (1997, cap 7) used PSID to show that in a similar context to ours, OLS using single year data produces the lowest estimates of β. OLS using averaged data raises the estimate of β. Finally, IV estimation raises the estimate of β yet further, so that the highest estimate is produced by IV and averaged data.

Two groups of instrumental variables are specified: Z (variables which are hypothesized to determine permanent earnings), and X (variables which are

TABLE 7

Summary of Main Findings

	Gini 1983	Gini 1995	S
Participants	0.501	0.461	0.554
Earners	0.391	0.381	0.421
Permanent			
Participants	0.188	0.216	0.220
Earners	0.202	0.219	0.174
Age-adjusted			
Participants	0.479	0.431	0.586
Earners	0.354	0.357	0.469
Longitudinal			
Participants	0.416		Na
Earners	0.349		

hypothesized to be correlated with reporting errors). Permanent earnings are defined to be $Y^*_{it} = Z_{it}\hat{\theta}_t$. The Z variables include 15 variables such as education, age,[12] gender, ethnicity and time since migration. The X variables include five variables such as inconsistencies in reported age between 1983 and 1995 and the number of missing variables. Because there are only two data points, no attempt is made to estimate fixed effects for individual i. These fixed effects should ideally form part of individual i's permanent earnings. The method of errors in variables with no fixed effects implies awkwardly that individuals with common Zs have equal permanent earnings, and that within group (i.e. controlling for common Zs) inequality in permanent income is zero. Permanent earnings and inequality change therefore either because the returns to Z change (i.e. β changes) or because Z changes (e.g. the individual acquired more education).

In the case of participants N = 16,275 and in the first stage regression R^2 = 0.0907 in 1983 and 0.1728 in 1995.[13] In the case of the employed in 1983 and 1995 N = 12,108 and R^2 = 0.1403 in 1983 and 0.2485 in 1995. Between 1983 and 1995 the returns to education increased, the conditional wage gap between Jews and non-Jews increased and the gender gap decreased.

The permanent Ginis (Table 7) for 1983 and 1995 for participants resulting from this exercise are 0.187 and 0.216. In the case of earners they are 0.216 and 0.219. These calculations[14] indicate two phenomena. First, permanent inequality, as measured by the method of errors in variables, is a fraction of its current counterpart. Recall that this most probably overstates the degree of equality due to the absence of fixed effects. According to Equation (12) permanent Gini must be less than current Gini. These calculations indicate that it is dramatically less. The second observation is that permanent inequality increased between 1983 and 1995

[12]Because age is used as an instrument, there is some overlap here with Section 4.1, where age-adjustment was the focus. However, age-adjustment is a separate issue that is dealt with in its own right.

[13]In 1995 CBS used auxiliary data from the National Insurance Institute to validate the earnings records in the Census. Hence, the 1995 earnings data are more accurate. Note that due to missing data for the Z and X variables the sample size for permanent earnings is smaller than it is for current earnings.

[14]When the X variables are omitted the permanent Ginis are 0.209 and 0.227 for participants and 0.217 and 0.234 for earners.

despite the fact that current inequality decreased. Note also, as expected, that permanent mobility is less than the mobility suggested by current earnings data. In the case of participants permanent *S* is 0.220 and for earners it is 0.174.[15] These findings are not sensitive to plausible changes in the choice of instruments.

4.3. *Permanent Beta Decomposition*

Table 3 discussed the relationship between quantity and rank mobility in earnings. The final row of Table 3 applies the decomposition in Equation (2) using permanent earnings data rather than current earnings data. The Gini estimate of permanent beta is 1.055, which implies that permanent earnings slightly diverged between 1983 and 1995, i.e. quantity mobility is almost zero. This compares with its current counterpart of 0.4932, implying that all the quantity mobility in current earnings is induced by transitory earnings.

The permanent measure of rank mobility is 0.779, which compares with its current measure of 0.4405. While permanent earnings are, as expected, less rank mobile than current earnings, they are not completely immobile. In contrast to the case of quantity mobility, where the transitory component of earnings accounted for all the observed mobility in current earnings, transitory earnings accounted for only about half of the rank mobility in current earnings.

Table 3 indicates that permanent earnings are less quantity mobile, partly because they are less rank mobile, and partly because there is Gini divergence in permanent earnings. Current earnings were more quantity mobile than rank mobile because current earnings were Gini convergent. By contrast, permanent earnings are more rank mobile than quantity mobile because permanent earnings are Gini divergent.

5. Disaggregation

The analysis thus far has referred to the population as a whole. Aggregate inequality may increase while inequality within major sub-groups of the population may decrease. Alternatively, the absence of changes in aggregate inequality may conceal important changes within groups. In this section account is taken of different demographic groups in the population.

Yitzhaki (1994) proposed the following relationship between the aggregate Gini coefficient and its components:

$$G_t = \sum_{1}^{J} P_{jt} O_{jt} G_{jt} + G_{bt} \tag{13}$$

where

$$P_{jt} = \frac{N_{jt}\overline{Y}_{jt}}{N_t\overline{Y}_t} = n_{jt}y_{jt}$$

$$O_{jt} = \frac{\mathrm{cov}_{jt}(Y, R)}{\mathrm{cov}_{jt}(Y, R_j)}$$

[15]When the X variables are omitted permanent S is 0.197 for participants and 0.159 for earners.

and where G_{jt} denotes the Gini coefficient within group j in time period t, P_{jt} denotes the share of group j in total income in period t, and O_{jt} is the coefficient of overlapping in period t, which measures the degree to which group j is included in the range of income as a whole in period t. If there is no overlapping at all, because the data are perfectly stratified, then $O_{jt} = N_{jt}/N_t$. G_{bt} denotes the between group Gini coefficient in period t.

The change in Gini, $\Delta G = G_2 - G_1$, may be decomposed via Equation (13) into the change that occurred due to: (a) changes in P_j and its sub-components, (b) changes in the within-group Ginis, (c) changes in the degree of stratification, and (d) changes in the between group Gini. Indeed, the overall Gini may not change, but this could conceal offsetting changes in the components in Equation (13). Sixteen subgroups are defined by gender, ethnicity, education and age. The variables in the decomposition include changes in the following variables for the 16 subgroups: population shares, relative average earnings, overlap coefficients, within-group Gini coefficients, and the intergroup Gini coefficient (G_b). Note that due to missing data (especially regarding education) only 18,620 observations out of the 20,454 participants in the study group are used.

The Gini coefficient in 1983 for this study group was 0.494 and in 1995 it was 0.460. While the change in Gini was not large, it may conceal gross changes that happened to offset each other. Such gross changes may be of interest in their own right.

The first cell in Table 8 shows that young, educated, Jewish men contributed 0.00144[16] to the change in Gini that occurred between 1983 and 1995, i.e. their contribution was positive. This contribution has a positive component and two negative components. The mean income of the group grew in relative terms, inducing an increase in Gini of 0.00712. However, the Gini coefficient for the group decreased, inducing a decrease in Gini of 0.00182. Finally, the overlapping coefficient for this group decreased because the group became more stratified, which induced a decrease in Gini of 0.00386. The Gini mobility index for this group is 0.69. Note that the share of the group in the total (N) does not change in the study group.

Although the overall Gini coefficient did not change very much, this results to some extent from offsetting contributions of the various components in Table 8. However, the fall in the overall Gini coefficient is largely accounted for by the fall in the Ginis for Jews, and especially the young, less educated ones. The largest negative contribution came from old, less-educated Jewish men. Table 8 shows that this resulted from a decline in their relative average earnings. Table 8 also shows that while earnings inequality decreased in the Jewish sector it slightly increased in the non-Jewish sector. Note also, that while Gini as a whole declined, inter-group inequality increased. This means that the decrease in intra-group inequality was greater than the increase in inter-group inequality.

[16]The contributions in Table 8 for ΔY, ΔO, and ΔG are multiplied for convenience by 100 in order to avoid an excessive number of zeros after the decimal point.

TABLE 8

GINI ACCOUNTING

Contributions	Total Jews	Total Non-Jews	ΔY Jews	ΔY Non-Jews	ΔO Jews	ΔO Non-Jews	ΔG Jews	ΔG Non-Jews	S Jews	S Non-Jews
Young educated men	0.144	0.013	0.712	–0.014	–0.385	0.018	–0.182	0.008	0.690	0.689
	1290	*104*								
Old educated men	–0.123	0	–0.201	0	–0.070	0	0.148	0	0.703	
	503	*23*								
Young educated women	–0.033	0	0.280	0	–0.032	0	–0.282	0	0.601	
	1231	*17*								
Old educated women	–0.206	0	–0.161	0	0.091	0	–0.136	0	0.576	
	278	*2*								
Young less educated men	–1.153	0.036	0.239	–0.006	–0.304	0.090	–1.088	–0.054	0.624	0.686
	5962	*1154*								
Old less educated men	–1.164	0.001	–1.049	–0.024	–0.130	0.017	–0.320	0.008	0.576	0.812
	1936	*206*								
Young less educated women	–1.167	0.013	0.076	0.006	–0.086	0.015	–1.154	–0.008	0.598	0.551
		4571	*162*							
Old less educated women	–0.034	0	–0.085	0	0.099	0	–0.048	0	0.526	
	1161	*20*								
Total	–3.736	0.063	–0.190	–0.038	–0.817	0.140	–3.210	–0.046		

Notes:
$\Delta G_b = 0.00152$. $G_b = 0.09497$ in 1983 and 0.09649 in 1995.
Number of observations given in italics.
Contributions have been multiplied by 100.
Young = aged 25–40 in 1983. Old = aged 41–50 in 1983.
Educated = above matriculation. Less educated = matriculation and below.

TABLE 9

EARNINGS INEQUALITY AND MOBILITY IN PSID

	Gini 1980	Gini 1992	Gini Mobility Index (S)
Participants			
Raw	0.367	0.422	0.465
Age-adjusted (N = 2,024)	0.327	0.389	0.486
Earners			
Raw	0.323	0.366	0.390
Age-adjusted (N = 1,770)	0.280	0.330	0.399

6. COMPARISON WITH PSID

It is difficult to compare earnings mobility in Israel with earnings mobility in other countries[17] for several reasons. First, the accounting period, time lapse and observation period should be the same, i.e. monthly, 12 years, and 1983–95 respectively, a combination that is difficult to find in practice. Secondly, mobility has to be measured using the same methodology. Since the methodology used here is new, there are no comparable measures for other countries. In the absence of suitable comparators individual earnings data for heads of households from PSID are used to calculate Gini mobility (S) over the 12-year period 1980–92.[18] For these purposes the calculation is restricted to individuals aged 20–50 years in 1980 so that it should be comparable to the data in the MCF study group. The results are reported in Table 9.

Table 9 shows that horizontal inequality in gross earnings increased between 1980 and 1992 in the U.S. regardless of whether the data are age-adjusted or not. However, the age-adjusted Gini for PSID tends to be smaller than its raw counterpart. Table 9 also shows that the Gini Mobility Index (S) is smaller in the U.S. than in Israel. For example, the Gini Mobility Index for all labor market participants is 0.465 in PSID, whereas its counterpart in MCD is 0.554. When the sample is limited to those reporting earnings in 1980 and in 1992 the Gini Mobility Index is 0.39 in PSID, whereas the counterpart in MCD is 0.421.

MCD does not allow us to calculate changes in earnings mobility because this requires panel data comprising more than two data points. So we cannot investigate whether mobility has been increasing or decreasing in Israel. By contrast PSID enables us to answer this question for the U.S. We find, for example that between 1970 and 1982, $S = 0.417$ for participants aged 22–48 in 1971, and $S = 0.322$ for earners. When these results are compared with Table 9, they imply that mobility in the U.S. increased between 1980 and 1992, compared with 1970–82.

7. CONCLUSIONS

This paper has two main objectives, methodological and descriptive. New methodologies were used to measure mobility and to decompose mean reversion.

[17]Gottschalk and Smeeding (1997) use the Luxembourg Income Study database to show that net individual income in Israel for 1992 had the 13th largest Gini out of 19 OECD countries, that P80/P20 for gross earnings ranked 2nd out of 9 countries for men and 4th out of 9 for women.

[18]Smith (1994), Hungerford (1993), and Veum (1992) also use PSID to investigate U.S. income mobility.

New data were used to measure various aspects of mobility and inequality in earnings in Israel. In doing so the distinction was made between current, permanent, longitudinal, and life-cycle (age-adjusted) earnings. A new measure of mobility, the Gini Mobility Index was used to measure earnings inequality in Israel. This index shows that 12-year earnings mobility is greater in Israel than it is in the U.S. It also shows that in the 1980s U.S. earnings were more mobile than in the 1970s. As is well known, mobility implies that horizontal measures of inequality overstate the underlying level of inequality. In the case of earnings in Israel the degree of overstatement is about 15 percent. This constitutes a lower bound because it is based on only two data points, and because additional panel data are unlikely to be colinear with the data for 1983 and 1995.

Paglin's suggestion to age-adjust the data makes only a small difference to measures of inequality and mobility. The reason for this is that age and related life-cycle variables explain such a small proportion of earnings. By contrast, "permanenting" the data makes a large difference. Permanent inequality and mobility are about half of their current counterparts, implying that transitory earnings account for the other half. Moreover, permanent inequality increased while current inequality decreased. These conclusions are qualified by the fact that because they are based on only two data points, permanent inequality may be overestimated.

Convergence, inequality and mobility are closely interwoven concepts even to the point of confusion. A new decomposition theorem was used to disentangle these concepts empirically. Mean reversion, or beta convergence, measures quantity mobility. It varies directly with rank mobility and with Gini convergence, and inversely with growth. This means that faster growing economies will experience less mean reversion, or for given rank and quantity mobility they will experience less Gini convergence. The results show that whereas mean reversion and Gini convergence occurred with currents earnings, mean diversion and Gini divergence occurred with permanent earnings.

Policy makers concerned with equality may draw comfort from the high degree of mobility, since conventional horizontal measures of inequality, reported, for example, by Dahan (2001) and in the Annual Poverty Report of the National Insurance Institute, overstate the underlying level of economic inequality. The results imply that there is most probably little that policy makers can do to change the underlying level of earnings inequality. Since R^2 for the earnings equations reported in Section 4.2 ranges between 0.09 and 0.25, it follows that the vast majority of earnings inequality is due to unobserved heterogeneity. It also follows that only a small fraction of earnings inequality stems from inequality in education. This means that a policy to promote earnings equality through education is bound to have almost no effect. According to the 1995 Census data, the Gini for years of education was 0.143 whereas the Gini for earnings was 0.409 (Table 2). The contribution of education inequality to earnings inequality, as calculated from a Gini income decomposition,[19] is as small as 5 percent, i.e. complete equality in

[19]The share is equal to $G_E S_E \mathrm{cor}(E,R)/G$ where G_E denotes the Gini for years of education, S_E denotes the return to education as a percentage of earnings, and cor(E, R) is the correlation between education and the rank of earnings. See Stark *et al.* (1986).

education would lower Gini for earnings from 0.409 to only 0.389. Presumably this result is not peculiar to Israel.

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