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Regional Heterogeneity, Conditional Convergence and Regional Inequality

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BEENSTOCK M. and FELSENSTEIN D. Regional heterogeneity, conditional convergence and regional inequality, *Regional Studies*. The paper stresses the importance of accounting for regional heterogeneity in the dynamic analysis of regional economic disparities. Studies of regional growth mainly presume that regions are homogeneous in their socio-demographic composition. It is argued that the analysis of regional convergence needs to be tested conditionally, i.e. conditional upon the socio-demographic structure of the workers in the various regions. To this end, various measures of conditional regional earnings inequality are estimated using Israeli regional data for the period 1991–2002. The results show that about half of regional earnings inequality may be accounted for by the conditioning variables. Conditioning also makes a large difference to estimates of Gini and beta-convergence. Conditional beta and Gini mobility are about half their unconditional counterparts.

Regional homogeneity Inequality Conditional convergence Mobility

BEENSTOCK M. and FELSENSTEIN D. 区域异质性，条件收敛和区域差异，区域研究。本文强调并解释了区域异质性在对区域经 济差异的动态分析中的重要性。区域增长研究主要假定区域在社会－人口构成上是均质的。本文认为，区域收敛（regional convergence）的分析需要对条件加以检验，比如不同区域工人的社会－人口结构条件。最后，文章运用了以色列地区1991年到 2002年期间的数据，评估多种考虑了条件变量的区域收入差异估算方法。结果表明，区域收入差异大约一半可以由条件变量加以 解释。加入条件变量后，对基尼系数和beta收敛（Gini and beta-convergence）的估算有很大的不同。考虑条件变量之后的beta和基 尼移动性（Gini mobility）差不多是它们在不考虑条件变量情况下的一半。

区域均质 差异 条件收敛 移动性（Mobility）

BEENSTOCK M. et FELSENSTEIN D. L'hétérogénéité régionale, la convergence sous condition et les écarts régionaux, *Regional Studies*. Cet article met l'accent sur l'importance de tenir compte de l'hétérogénéité régionale dans l'analyse dynamique des écarts régionaux économiques. En règle générale, les études sur la croissance régionale laissent supposer que la structure socio-démographique des régions est homogène. On cherche ici à affirmer que l'analyse de la convergence régionale doit être tester sous condition, telle la structure socio-démographique des travailleurs dans les diverses régions. Dans ce but, on estime plusieurs mesures de l'écart des salaires régionaux sous condition à partir des données israéliennes pour la période de 1991 à 2002. Les résultats laissent voir que la moitié de l'écart des salaires régionaux environ s'explique par les conditions posées. Poser des conditions influe sensiblement sur les estimations de convergence Gini et béta. Les mobilités béta et Gini sous condition se chiffrent à environ la moitié de leurs équivalents sans condition.

Hétérogénéité régionale Ecart Convergence sous condition Mobilité

BEENSTOCK M. und FELSENSTEIN D. Regionale Heterogenität, konditionale Konvergenz und regionale Unterschiede, *Regional Studies*. In diesem Beitrag wird die Bedeutung einer Berücksichtigung der regionalen Heterogenität bei einer dynamischen Analyse der regionalen wirtschaftlichen Disparitäten betont. In den meisten Studien zum Regionalwachstum wird davon ausgegangen, dass Regionen hinsichtlich ihrer soziodemografischen Zusammensetzung homogen sind. Wir argumentieren, dass die Analyse der regionalen Konvergenz konditional überprüft werden muss, d.h. in Abhängigkeit von der soziodemografischen Struktur der Arbeitnehmer in den verschiedenen Regionen. Zu diesem Zweck schätzen wir die verschiedenen Maßstäbe für die konditionalen regionalen Einkommensunterschiede mit Hilfe von Regionaldaten aus Israel für den Zeitraum von 1991 bis 2002. Aus unseren Ergebnissen geht hervor, dass sich etwa die Hälfte der regionalen Einkommensunterschiede auf die konditionierenden Variablen zurückführen lässt. Die Konditionierung macht auch bei den Schätzungen des Gini-Koeffizienten und der

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Beta-Konvergenz einen erheblichen Unterschied. Die konditionale Beta- und Gini-Mobilität beträgt etwa die Hälfte ihrer nicht konditionalen Vergleichswerte.

Regionale Homogenität Ungleichheit Konditionale Konvergenz Mobilität

BEENSTOCK M. y FELSENSTEIN D. Heterogeneidad regional, convergencia condicional y desigualdades regionales, *Regional Studies*. En este ensayo recalcamos la importancia de tener en cuenta la heterogeneidad regional en el análisis dinámico de las desigualdades económicas a nivel regional. En los estudios de crecimiento regional se supone principalmente que las regiones son homogéneas en su composición sociodemográfica. Sostenemos que debe comprobarse condicionalmente el análisis de la convergencia regional, es decir, condicional en la estructura sociodemográfica de los trabajadores en las diferentes regiones. Con este fin calculamos las diferentes medidas de las desigualdades salariales condicionales en las regiones usando datos regionales de Israel durante el periodo de 1991 a 2002. Nuestros resultados indican que aproximadamente la mitad de las desigualdades salariales regionales se deben a variables condicionales. Este acondicionamiento también muestra grandes diferencias en los cálculos del índice Gini y la convergencia beta. La movilidad condicional de beta y Gini representan casi la mitad de su equivalentes incondicionales.

Homogeneidad regional Desigualdad Convergencia condicional Movilidad

JEL classifications: D63, O18, R12

INTRODUCTION

The empirical literature on regional growth convergence has implicitly assumed that the labour force is homogeneous between regions (e.g. BARRO and SALA-I-MARTIN, 1991; TSIONAS, 2000, CUADRADO-ROURA *et al.*, 1999, among many others). Homogeneity does not mean here that individual workers are identical across regions since workers vary by age, education, ethnicity, etc. Instead, it means that individual heterogeneity tends to average out in large populations so that, for example, average age tends to be similar between regions. The present paper makes the case that the analysis of regional economic growth needs to account for regional heterogeneity.

Regional homogeneity implies that wages in different regions should converge upon some common value. Suppose, however, that the labour force is in fact heterogeneous between regions in terms of its socio-demographic composition. Human capital theory does not predict in this case that real wages will be equated interregionally. Instead it predicts that real wages will tend to be higher in regions where there is a greater concentration of human capital, where workers have more experience, and where there are smaller concentrations of workers who typically earn less, mainly women, ethnic minorities, and young workers. The growth convergence hypothesis must therefore be tested conditionally, i.e. conditional upon the socio-demographic structure of the workers in the various regions.

A number of recent studies[1] have broken new ground by conditioning upon workers' characteristics in testing hypotheses about regional convergence. They find that conditional regional inequality is smaller than its unconditional counterpart.[2] They (with the exception of COMBES *et al.*, 2007) also attach importance to regional differences in the cost of living (COL) These have been typically ignored in the empirical literature despite the fact that they reduce measured regional inequality (BEENSTOCK and FELSENSTEIN, 2007).[3] Conditional regional earnings deflated by regional COLs are relevant to comparisons of economic well-being between regions. Regional COLs fulfil the function intra-nationally that the use of 'purchasing power parity' exchange rates fulfil internationally (SUMMERS and HESTON, 1991).

In summary, measures of regional inequality that take into account regional differences in socio-demographics as well as regional differences in living costs may be quite different to measures that ignore these differences. In addition, tests of regional convergence that ignore these differences may generate quite different results to tests that condition upon these regional differences. This paper distinguishes between two types of convergence: sigma-convergence and beta-convergence. However, since the paper diverges from the literature by measuring measure regional inequality by Gini rather than the standard deviation, it distinguishes between Gini-convergence and Gini mobility. Indeed, it is shown that using Gini measures of beta-convergence provides a richer framework for investigating convergence than conventional ordinary least-squares (OLS) measures.

The paper proceeds as follows. The methodology for estimating regional conditional earnings is first presented. In doing so, the paper distinguishes between the concepts of mobility, beta-convergence and Gini-convergence. Data for Israel are used for 1991–2002 to estimate various measures of conditional regional wage inequality. The results suggest that much of the regional inequality in earnings in Israel may be accounted for by the conditioning variables. Indeed, whereas there is regional Gini-divergence in unconditional wages, conditional wages display regional Gini stability.

The paper also investigates the empirical implications of regional heterogeneity for beta-convergence in regional earnings. Beta-convergence is concerned with mobility since it predicts that earnings grow faster in regions with below-average earnings and slower in regions with above-average earnings. The former are upwardly mobile and the latter are downwardly mobile. The Gini Mobility Index (GMI) is used to distinguish between relative and absolute mobility by taking account of the level of regional earnings as well as the position of regions in the distribution. It is shown that while there is greater regional mobility in unconditional earnings, this conceals a low degree of inherent regional mobility. The results show that up to half the mobility in regional earnings comes from socio-demographic characteristics. Therefore, ignoring regional heterogeneity may lead not only to serious over-estimation of the underlying level of regional inequality, but also to erroneous conclusions regarding its trend.

These results join a small but growing body of evidence which suggests that regional heterogeneity matters. The law of large numbers, which predicts that regions are probably sufficiently large and diverse to be homogeneous, does not apply in Brazil, the UK, France, and even in small countries such as Austria and Israel. These results suggest that the widespread practice of testing for regional growth convergence without conditioning upon the socio-demographic and economic structure of the regions concerned is likely to be misleading. It is also shown that it is important to take account of COL differentials in the empirical analysis of regional convergence.

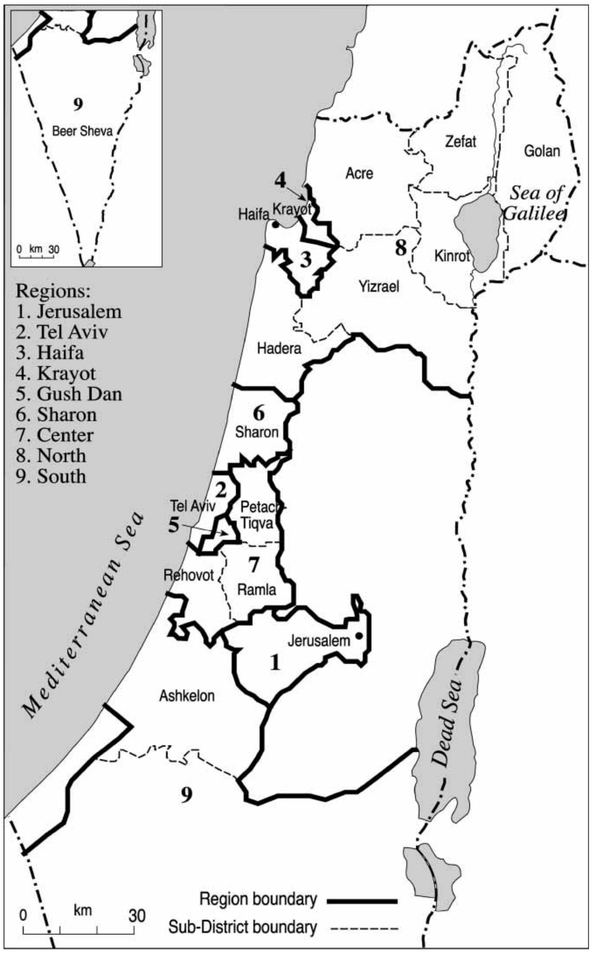

Fig. 1. Geographic regions of Israel

REGIONAL HETEROGENEITY IN ISRAEL

PORTNOV and ERELL (2003) showed that the social and demographic composition of Israel's regions is markedly heterogeneous. They surveyed regional distributions of a large body of diverse indicators finding spatial divergence over time in some (population, income distribution, labour force participation) and convergence in others (education, housing density, etc.). A cross-sectional picture for wage earners highlighting select socio-demographic differences is presented in Table 1 for 1995. The data come from the Household Income Survey (HIS) conducted annually by the Central Bureau of Statistics (CBS), covering roughly 13 000 respondents. Table 1 shows that in 1995 the average age of earners was 40.19 years in Haifa and only 35.04 years in the North (Fig. 1). Earners in Jerusalem had 14.16 school years, whereas earners in the North had on average only 11.31 years of schooling. Women accounted for 53.3% of earners in Jerusalem, whereas they accounted for only 35.8% in the North. Almost half the workers in the North were non-Jewish, whereas only 1% of workers in Jerusalem were non-Jewish.[4]

Average monthly earnings varied substantially between the regions; there is a 40% difference between top-ranked Tel Aviv and bottom-ranked Northern region. Ostensibly, these are very large regional differences. However, they do not condition on the socio-demographic composition of the regions themselves. This paper examines whether these regional differences in earnings still persist after conditioning on the socio-demographics of the regions.

Table 1. Regional heterogeneity for 1995

	Age (years)	Years of schooling	Per cent non-Jewish	Per cent women in the labour force
Jerusalem	36.67	14.16	1.06	53.32
North	35.04	11.31	49.05	35.77
Haifa	40.19	13.21	8.95	47.59
Sharon	37.55	12.48	13.29	44.19
Center	38.47	13.07	3.15	48.69
Tel Aviv	37.47	13.15	3.58	48.79
Dan	38.66	12.81	1.16	48.39
South	37.79	12.41	4.63	47.74
Average[a]	37.67	12.73	11.98	46.41

Note: [a]All variable averages are non-weighted and represent averages in the Household Income Survey for 1995.

Although Israel's regions are demographically heterogeneous, there is no apparent spatial pattern to this heterogeneity. Moran's I statistic is usually used to measure spatial clustering. It is calculated using contiguous weights across the nine regions for two key variables: average years of schooling and average age. This is carried out for each year between 1991 and 2002 making 24 Moran's I statistics altogether. None of these approached statistical significance, suggesting that regional heterogeneity does not have any spatial pattern in Israel.[5]

METHODS

This section describes the methodology for estimating conditional earnings by region. The relationship between the interwoven concepts of mobility, beta-convergence and Gini-convergence is also discussed. In doing so, it distinguishes between relative and absolute concepts of mobility in regional earnings.

Conditioning for regional heterogeneity

To estimate conditional differences in regional earnings, 'Mincer models' are estimated using microdata[6] in which the labels 'i', 'r' and 't' refer to the individual, the region in which s/he lives, and the year of observation, respectively; and X is a vector of socio-demographic controls:

$$\ln W_{it} = \alpha_t + X_{it}\beta_t + \sum_{r=1}^{R} \delta_{rt} D_{ri} + \varepsilon_{it} \qquad (1)$$

where $D_{ri} = 1$ if individual i lives in region r and zero otherwise; and ε_{it} is the residual error with variance σ_t^2. Had there been panel data for individuals, and had these individuals remained in the same region, it would have been possible to estimate specific effects for these individuals, which would have enabled the authors to condition on observed as well as unobserved heterogeneity. For example, if abler people happen to live in a region, it would look as if the regional effect was greater simply because more able people happen to be living there. Clearly, such panel data would provide more informed estimates of conditional regional earnings. However, if individuals are mobile, and they are observed in different regions in the panel sample, it becomes more difficult to estimate individual specific effect since this requires dealing with self-selection problem in migration. COMBES *et al.* (2007) used French panel data for individuals to estimate conditional regional earnings, but do not take account of the inter-regional mobility problem already mentioned.

Unlike Combes *et al.*, the present paper does not have panel data for individuals. Equation (1) is therefore estimated for year t using survey data for that year. The estimate of δ_{rt} represents the conditional effect on earnings due to living in region r at time t. Note that in equation (1) the conditional trend in wages is expressed by α_t, and the coefficients of the X variables vary over time. Equation (1) follows AZZONI and SERVO (2002), MAIER and WEISS (1986) and COMBES *et al.* (2007) in assuming that the β's do not vary by region.[7]

The X variables include standard 'Mincer' variables such as age, age squared, and years of schooling. The authors also controls for economic branch and occupation since conditional earnings are likely to vary between occupations and economic branches. Finally, gender and ethnicity are controlled, where the latter takes account of wage gaps between Jews and non-Jews, and between first- and second-generation immigrants and natives (CHISWICK, 1998).

Out of these controls only age, sex, and religion are exogenous. In principle, individuals choose their occupation, where they work, marital status, and their education. They also choose where they live. Therefore, the regional dummy variables specified in equation (1) are also potentially endogenous. If inhabitants in region r are positively/negatively self-selected, then δ_r will be over-/underestimated. In this case δ_r embodies the causal effect upon earnings due to living in region r, and a selection effect due to the people who happen to choose to live in region r.

This means that separate instrumental variables are required for each of these potentially endogenous variables. For example, in the case of the regional dummies one would require variables that affect choice of residence without directly affecting earnings,[8] and without directly affecting education and other potentially endogenous variables. Short of credible instruments, such as region of birth in the case of place of residence, and information on parents in the case of education, the issue of potential endogeneity in equation (1) cannot be convincingly treated. Nevertheless, Heckman's selection method is used (HECKMAN, 1979), which does not require instrumental variables, to test for evidence of regional selectivity at given points in time. As is well known, identification of selectivity by this method is entirely parametric and therefore loses much of its conviction. The fact that place of residence is endogenous does not automatically mean that estimates of δ_r must be inconsistent. If place of residence is neutrally selected, then estimates of δ_r will be consistent. Neutral selection occurs when unobserved heterogeneity in earnings (ε in equation 1) is independent of unobserved heterogeneity in selection.

Selection bias means that wages in a region may be relatively high simply because abler workers happen to have chosen to work there, i.e. they are positively selected, and not because the productivity of workers in that region happens to be inherently higher. Insofar as there is selectivity into occupations and economic branches, the δ's derived from equation (1) are estimated net of this type of selectivity. Matters would have been quite different had one not controlled for occupation and economic branch. The question therefore remains whether for given occupations and economic branches there is unmeasured regional self-selectivity.

If such residual regional self-selectivity exists, the estimates of absolute conditional earnings may be over- or understated. However, if this selection bias happens to be stable over time, the estimated changes in conditional regional earnings will be free of selection bias. Therefore, the authors are more confident about the development of conditional regional earnings over time than about absolute comparisons between regional earnings at a given point in time.

Equation (1) implies that the expected value of earnings in region r at time t is:

$$E(W_{rt}) = \exp\{\alpha_t + X_{rt}\beta_t + \delta_{rt} + \tfrac{1}{2}\sigma_t{}^2\} \qquad (2)$$

Equation (2) shows that expected wage growth in region r derives from several sources.

- It varies directly with the change in α, which captures the national trend in wage growth.
- It varies directly with the national change in β, which captures the change in the returns to characteristics, such as an increase in the return to education.
- Expected wage growth depends upon the regional change in these characteristics, e.g. the level of education in the region increases.
- It varies directly with the change in δ_r, which captures the change in return to living in region r.
- Finally, if the unexplained variance of earnings increases expected wage growth will be larger.

In short, equation (2) can be used to decompose regional earnings growth into these five components.

Having estimated equation (1) its parameters can be substituted into equation (2). Several applications of equation (2) are suggested. The first is to calculate the basic return to earnings in region r in time t. It is equal to $\alpha_t + \delta_{rt}$. This is referred to as the basic regional wage, which deducts from regional earnings growth the second and third components. The second is the conditional regional wage, which is equal to:

$$\alpha_t + \delta_{rt} + X_0\beta_t$$

where X_0 is the average regional characteristics in the base year. The conditional regional wage normalizes regional earnings to a common and constant socio-demographic norm. It simulates the wage in region r at year t that would be expected had the socio-demographics of region r in year t been held constant at the average level in the base year. Conditional regional wage growth is therefore equal to basic regional wage growth plus wage growth due to the change in returns to characteristics. A further application is to decompose regional wage differentials in year t into contributions due to regional differences in the conditioning variables. In year t this is equal to $(X_{rt} - X_t)\beta_t$.

Following Juhn *et al.* (1993), the present paper uses the Mincer model to distinguish between within- and between-group inequality in log earnings. Within-group inequality is measured by the estimate of σ_t^2, whereas between-group inequality is measured by total inequality (the variance of $\ln W_t$) minus within-group inequality. Within-group inequality reflects the return to general ability, whereas between-group inequality reflects the return to observable socio-demographic characteristics such as education. Note that R^2 measures the share of between-group inequality in total inequality.

Mobility, beta-convergence and Gini-convergence

Beta has probably served as the most popular measure of mobility. Beta-convergence, or mean reversion, implies that earnings grow faster than average in regions with below-average earnings, and slower than average in regions with above-average earnings. This implies that log earnings are upwardly mobile in the former group and downwardly mobile in the latter. Mobility here refers to absolute mobility in earnings. If earnings were perfectly immobile, beta would be unity and earnings would be expected to grow at the same rate everywhere.

Another type of mobility refers to the rank or position of a region in the national distribution, which is a relative measure of mobility. Upward mobility in the absolute sense may or may not coincide with upward mobility in the relative sense. For example, earnings in a region may grow faster than the average (upward absolute mobility) while its rank in the distribution happens to fall (downward rank mobility) or vice versa. The two types of mobility are of course related.

Yitzhaki and Wodon (2004) are followed in exploring the relationship between absolute and relative mobility. In what follows W_{rt} denotes conditional earnings in region r at time t. The OLS estimator for β_t is obtained by regressing W_{rt} on W_{rt-1} using cross-section data. However, since Gini is used to measure regional inequality, the authors prefer to use the Gini estimator for β_t, which uses the rank of W_{rt-1}, denoted by $R_{rt-1} = F(W_{rt-1})$ rather than W_{rt-1}:

$$\beta_t = \frac{\text{cov}(W_{rt}R_{rt-1})}{\text{cov}(W_{rt-1}R_{rt-1})} \qquad (3)$$

The Gini estimator can be regarded as an instrumental variables estimator since it uses the rank to instrument the level. Since the rank of W is typically measured more accurately than W itself, β is arguably a superior estimator to its OLS counterpart.

Following SCHECHTMAN and YITZHAKI (1987) Gini may be defined as:

$$G_t = \frac{2\mathrm{cov}(W_{rt}, R_{rt})}{\overline{W}_t} \tag{4}$$

where G_t is the Gini coefficient measuring regional inequality at time t. The Gini correlation between W in period t and its rank in period $t-1$ is defined as:

$$\Gamma_{t.t-1} = \frac{\mathrm{cov}(W_{rt}, R_{rt-1})}{\mathrm{cov}(W_{rt}, R_{rt})} \tag{5}$$

and is bounded between 1 and -1. It measures (backward) relative mobility. W is perfectly relatively immobile when $\Gamma = 1$. If $\Gamma = 0$ there is random relative mobility because it is not possible to infer R_{rt-1} using information on W_{rt}. For all practical purposes this represents the case of complete mobility. When $\Gamma = -1$ there is perfectly perverse mobility: the top-ranked exchanges places with the bottom ranked, the second to top exchanges places with the second from the bottom, and so on.

Substituting equations (4) and (5) into equation (3) gives rise to the following decomposition theorem for beta:

$$\beta_t = \Gamma_{t.t-1}\frac{G_t}{G_{t-1}}\frac{\overline{W}_t}{\overline{W}_{t-1}} \tag{6}$$

Equation (6) shows that beta, which measures absolute immobility, depends upon three factors. It varies directly with (backward) relative immobility ($\Gamma_{t.t-1}$). It also varies inversely with the degree of Gini divergence as measured by G_t/G_{t-1}. Finally it varies directly with the rate of levelling-up as measured by $\bar{W}_t \;/\; \bar{W}_{t-1}$, which exceeds unity in the event of levelling-up and aggregate growth, and is less than unity in the event of levelling down. If all three components happen to equal unity, i.e. there is no relative mobility, Gini is stable and there is neither levelling up or down, then $\beta = 1$ and the rate of mean reversion is zero. When $G_t = G_{t-1}$ and $\bar{W}_t = \bar{W}_{t-1}$, equation (6) implies that $\beta = \Gamma$, i.e. relative mobility and absolute mobility are identical when Gini is stable and there is no levelling up or down. In general, however, the two measures of mobility differ. Indeed, beta may exceed unity when gamma is less than unity and vice versa. If $\Gamma = 0$, then $\beta = 0$ regardless of the rates of Gini-convergence and levelling. Equation (6) implies that one cannot infer Gini-convergence or divergence from beta-convergence or divergence, and vice versa.

Note that in general $\Gamma_{t.t-1}$ differs from $\Gamma_{t-1.t}$, i.e. backward and forward measures of relative mobility differ. The problem is similar to the common index number effect, where, for example, the rate of inflation depends upon the direction of measurement. YITZHAKI (2003) has suggested a symmetric Gini mobility index (GMI), which weights the forward and backward measures of relative mobility, defined as:

$$S_t = \frac{G_{t-1}(1-\Gamma_{t-1.t}) + G_t(1-\Gamma_{t.t-1})}{G_{t-1}+G_t} \tag{8}$$

where S is naturally bounded between zero (no relative mobility) and 2 (perfectly perverse mobility). When $S = 1$, relative mobility is random. This is the measure of relative mobility that is used below in discussing regional mobility and beta coverage.

MINCER MODELS, 1991–2002

The Household Income Survey (HIS) is used to estimate equation (1). Following BEENSTOCK and FELSENSTEIN

Table 2. Illustrative wage regression for 1995

Variable	Coefficient	Robust standard error (SE)	SE
Constant	4.843	0.147	0.142
Education	0.025	0.003	0.003
Age	0.075	0.007	0.006
Age-squared	−0.001	0.000	0.000
Non-Jewish	−0.046	0.028	0.031
Male	0.518	0.019	0.019
Marital status	0.136	0.023	0.021
Last school (Yeshiva)	−0.659	0.097	0.088
Br1 – Agriculture	0.114*	0.091	0.076
Br2 – Industry	0.322	0.047	0.041
Br3 – Electricity plus water	0.323	0.051	0.047
Br4 – Construction	0.385	0.052	0.048
Br5 – Commerce, hotels	0.295	0.047	0.041
Br6 – Transport plus communications	0.560	0.048	0.044
Br7 – Finance	0.382	0.047	0.040
Br8 – Public plus community services	0.221	0.046	0.039
Occ1 – Academic	0.891	0.044	0.041
Occ2 – Technicians	0.706	0.040	0.037
Occ3 – Managers	1.113	0.047	0.046
Occ4 – Clerks	0.578	0.036	0.034
Occ5 – Sales plus service	0.227	0.038	0.034
Occ6 – Farm workers	0.381	0.037	0.037
Occ7 – Skilled industrial	0.232	0.038	0.037
Jerusalem	0.041*	0.055	0.051
Tel Aviv	0.159	0.052	0.049
Haifa	0.034*	0.055	0.051
Dan	0.076*	0.050	0.047
Center	0.123	0.049	0.046
South	0.018*	0.051	0.048
Sharon	0.089*	0.060	0.039
North	0.061*	0.051	0.048

Notes: All coefficients are significant at $p < 0.05$, unless indicated (*).
Adjusted $R^2 = 0.387$; $n = 6279$.
Equation standard error = 0.385.
White test for heteroskedasticity = 138.8, $X^2_{0.05} = 18.5$.
Moran's I for spatial autocorrelation = 0.342; $p = 0.244$.
F-tests: regional homogeneity for education = 1.76, $F_{8,6240} =$ 1.94; regional homogeneity for age = 2.81; $F_{8,6240} = 1.94$.

Table 3. Coefficients for key socio-demographic indicators

Socio-demographic indicators	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Education	0.019*	0.024*	0.014*	0.018*	0.025*	0.026*	0.078*	0.073*	0.084*	0.084*	0.066*	0.032*
Age	0.081*	0.079*	0.065*	0.082*	0.074*	0.073*	0.027*	0.026*	0.025*	0.027*	0.036*	0.078*
Non-Jewish	0.049	0.033	−0.013	−0.013	−0.044	−0.023	−0.062	−0.144*	−0.125*	−0.162*	−0.131*	−0.092*
Male	0.552*	0.562*	0.569*	0.560*	0.525*	0.483*	0.542*	0.529*	0.511*	0.517*	0.487*	0.505*
Marital status	0.086*	0.120*	0.100*	0.195*	0.142*	0.174*	0.120*	0.114*	0.146*	0.127*	0.152*	0.191*
Yeshiva	−0.345*	−0.355*	−0.467*	−0.707*	−0.664*	−0.699*	−0.479*	−0.504*	−0.720*	−0.667*	−0.748*	−0.766
Total inequality	0.588	0.643	0.626	0.659	0.628	0.653	0.634	0.623	0.653	0.657	0.654	0.659
Within-group inequality	0.381	0.414	0.402	0.416	0.388	0.405	0.401	0.390	0.396	0.394	0.388	0.420
Between-group Inequality	0.207	0.229	0.224	0.243	0.240	0.248	0.233	0.233	0.257	0.263	0.266	0.239
n	5618	5502	5014	5558	6279	6008	10294	10419	11608	11904	11806	12608
R^2	0.351	0.354	0.358	0.368	0.381	0.378	0.365	0.372	0.391	0.399	0.405	0.362

Note: *Significant at $p < 0.001$.

(2007), the present paper divides Israel into nine regions, which are illustrated in Fig. 1. The analysis for the years 1991–2002 is carried out. The X variables include age and its square, years of schooling, seven occupational dummies, eight economic sectoral dummies, nine regional dummies, and dummies for marital status, Jews, males, and yeshiva students. The last variable (BERMAN, 2000) refers to ultra-orthodox Jews whose years of learning are of little practical use. Hopefully, these variables capture a broad range of variables identified by labour economists in Israel. The base region is the Krayot, which is a group of towns near Haifa.

Table 2 reports an illustrative estimate of equation (1) for 1995.[9] Robust and regular standard errors turn out to be quite similar, despite the fact that there is evidence of heteroskedasticity. A test for regional heterogeneity in the coefficients for schooling and age suggests that one can safely assume that these coefficients are homogeneous. Moran's I statistic has also been calculated as -0.342 for panel data using the average residuals by region, which suggests that the residuals are negatively spatially autocorrelated. However, this is not statistically significant.[10]

Table 3 reports estimates of some key beta-coefficients over time and measures of inequality. The former include age, sex, years of schooling, marital status, education level, and ethnic/religious grouping. With the exception of 'non-Jew' during 1991–97, all covariates are statistically significant across the period and R^2 rises from 0.35 in 1991 and peaks at 0.40 in 2001, suggesting the growing importance of between group inequality in total

Table 4. Regional coefficients over time

Regions	Meta-statistics	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Jerusalem	24.94	−0.114*	0.062	−0.030	−0.107	0.042	−0.002	0.044	−0.018	0.053	0.035	−0.042	−0.039
		(0.053)	(0.057)	(0.055)	(0.054)	(0.050)	(0.051)	(0.039)	(0.037)	(0.039)	(0.038)	(0.038)	(0.037)
Tel Aviv	89.94**	0.008	0.203*	0.068	0.061	0.154*	0.071	0.149*	0.078*	0.145*	0.182*	0.150*	0.117*
		(0.050)	(0.054)	(0.052)	(0.052)	(0.048)	(0.049)	(0.036)	(0.035)	(0.038)	(0.037)	(0.036)	(0.037)
Haifa	15.67	−0.104	0.129*	−0.032	−0.034	0.026	−0.039	0.062	−0.015	0.002	0.058	−0.005	−0.100*
		(0.054)	(0.058)	(0.057)	(0.057)	(0.051)	(0.057)	(0.039)	(0.038)	(0.040)	(0.054)	(0.038)	(0.038)
Dan	20.01	−0.038	0.089	0.017	−0.001	0.076	−0.015	0.087*	−0.012	0.087*	0.058	0.042	0.033
		(0.049)	(0.052)	(0.050)	(0.051)	(0.047)	(0.046)	(0.036)	(0.034)	(0.037)	(0.036)	(0.035)	(0.036)
Center	69.24**	0.014	0.201*	0.059	0.023	0.124*	0.025	0.121*	0.060	0.117*	0.115*	0.100*	0.095*
		(0.047)	(0.050)	(0.049)	(0.049)	(0.046)	(0.045)	(0.035)	(0.033)	(0.035)	(0.034)	(0.034)	(0.034)
South	45.91*	−0.108*	0.082	−0.066	−0.104*	0.026	−0.086	0.007	−0.102*	−0.035	−0.042	−0.041	−0.071*
		(0.051)	(0.058)	(0.052)	(0.051)	(0.048)	(0.047)	(0.035)	(0.034)	(0.037)	(0.030)	(0.035)	(0.035)
Sharon	29.11	−0.144*	0.078	−0.073	0.010	0.086	−0.145*	−0.023	−0.022	0.025	0.007	−0.025	0.019
		(0.060)	(0.062)	(0.062)	(0.064)	(0.058)	(0.058)	(0.046)	(0.042)	(0.042)	(0.042)	(0.041)	(0.043)
North	28.27	−0.043	0.025	−0.083	−0.115*	0.066	−0.073	0.014	−0.069*	0.009	0.003	−0.006	−0.064
		(0.051)	(0.054)	(0.052)	(0.052)	(0.063)	(0.047)	(0.037)	(0.035)	(0.036)	(0.036)	(0.035)	(0.035)

Notes: Standard errors are in parentheses.
*Significant at $p < 0.05$.

inequality. Overall earnings inequality has remained broadly unchanged, but within-group inequality declined slightly and between-group inequality increased.

Note that the coefficient on education (as measured by years of schooling) is conditional upon occupation, which in some years mediates most of the effect of education upon earnings. Table 3 indicates that this conditional return to education increased substantially in the second half of the 1990s. By contrast, the opposite happened to age; the age premium was lower in the second half of the decade. The gap between the earnings of Jews and non-Jews widened by about 15% over the period, while the large wage advantage of males remained stable. Finally, the wage disadvantage of yeshiva graduates doubled over the period.

Table 4 reports the full set of delta-coefficients, which index conditional relative regional earnings. The picture here is ostensibly more volatile than in Table 3 with some regional coefficients switching direction of signs and levels of significance over the 12-year period.[11] However, only 29 out of the 96 coefficients reported in Table 4 are statistically significant, of which Tel Aviv and the Center account for 15 coefficients. These coefficients for Tel Aviv and the Center are consistently positive. The coefficients for the South are in the main negative over the period and are generally insignificant. Note that this classification on the whole does not depend upon the use of robust standard errors[12] since robust and regular standard errors turn out to be similar.

The important conclusion arising out of Table 4 is that for the most part conditional regional wage differentials are zero. To investigate this matter more thoroughly, two separate statistical tests are presented. In the first, the Mincer model is re-estimated for year t with zero restrictions on regional dummy variables ($\delta_{rt} = 0$ given t), and using an F-test to retain the regional dummy coefficients that are statistically significant. In the second, the results presented in Table 4 are used to test the restriction that the dummy variables for a given region are not significantly different from zero over time ($\delta_{rt} = 0$ given r). The inverse chi-square meta-statistic is used (HEDGES and OLKIN, 1985):

$$A_r = -2\sum_{t=1}^{T} \ln(P_{rt}) \approx \chi^2_{2T}$$

where P_{rt} is the p-value of the estimated δ_{rt}. If A_r exceeds the critical value of the chi-square, then one can reject the hypothesis that $\delta_{rt} = 0$ in region r. These meta statistics are reported in Table 4, which shows that only in Tel Aviv, the Center, and the South are these regional dummy variables systematically significant.

Table 5 reports the estimates of these regional dummy variable coefficients and their confidence intervals that survive the F-tests mentioned above. In Tel Aviv earnings are between 9 and 18% higher than in the base regions, while in the South they are about 3–12% lower. Note also that these estimates are robust with respect to the

Table 5. *Regional dummy coefficients (confidence limits are in brackets) for the restricted model*

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Jerusalem	−0.106 [−0.165 − 0.046]			−0.124 [−0.186 − 0.062]					0.058 [0.014 0.101]			−0.063 [−0.110 − 0.018]
Tel Aviv		0.129 [0.076 0.182]	0.096 [0.040 0.152]		0.110 [0.060 0.159]	0.073 [0.022 0.124]	0.127 [0.088 0.166]	0.092 [0.052 0.133]	0.151 [0.109 0.192]	0.183 [0.143 0.223]	0.173 [0.132 0.213]	0.093 [0.047 0.139]
Haifa	−0.094 [−0.158 − 0.030]											−0.125 [−0.175 −0.074]
Dan							0.066 [0.029 0.103]		0.093 [0.055 0.130]	0.060 [0.024 0.096]	0.065 [0.030 0.101]	
Center		0.129 [0.088 0.170]	0.089 [0.044 0.133]		0.074 [0.035 0.114]		0.100 [0.068 0.133]	0.074 [0.042 0.107]	0.123 [0.092 0.153]	0.117 [0.088 0.146]	0.123 [0.094 0.152]	0.071 [0.037 0.106]
South	−0.099 [−0.151 − 0.046]		−0.036 [−0.094 0.021]	−0.121 [−0.174 − 0.069]		−0.087 [−0.135 − 0.038]		−0.089 [−0.127 − 0.051]				−0.096 [−0.136 − 0.056]
Sharon	−0.134 [−0.216 − 0.051]					−0.144 [−0.229 − 0.066]		−0.056 [−0.056 − 0.016]				
North				−0.130 [−0.185 − 0.077]		−0.071 [−0.142 − 0.020]						−0.088 [−0.128 − 0.048]
Krayot												

specification of the Mincer model. If economic branch and occupation are dropped from the Mincer model, the results in Table 4 remain broadly the same. For example, in 1995 the coefficient for Tel Aviv is 0.198 instead of 0.154, and the coefficient for the Center is 0.144 instead of 0.124. However, these variables should not be omitted because the estimated regional effect should control for them. If earnings are higher in a region simply because the region has a concentration of high-paying occupations or branches, this should not be attributed to the region. Why some regions attract certain occupations and types of economic activity is not discussed here.

As noted in the third section, the specification of occupation and economic branch will mediate some of the effects of potential selection bias in the estimation of regional effects. To investigate the presence of selectivity in the estimated regional effects, Heckman's procedure, as discussed in the Methods section, was applied.[13] Since there are nine regions, this requires a multinomial probit selection specification. In view of the major computation burden that this entails, matters were simplified by turning the problem into a simple probit model. A dummy variable is specified in the wage equation if the individual lives, say, in Tel Aviv, and a probit model is estimated bilaterally to explain this dummy variable. When using data for 1995, no evidence of a significant selection bias for wage earners in Tel Aviv is found. This procedure is repeated for each of the regions using data for 1995. In none of the cases is evidence found of selection bias. This implies that the estimates of the regional dummy coefficients reported in Table 5 are most probably not picking up selection effects, but are capturing intrinsic differences in regional earnings.

CONDITIONAL REGIONAL INEQUALITY AND SIGMA-CONVERGENCE

This section uses the results obtained in the previous section regarding conditional regional earnings to carry out the following exercises. First, unconditional and conditional regional earnings were compared over time. This comparison reveals the importance of controlling for the observed characteristics of regional labour forces when

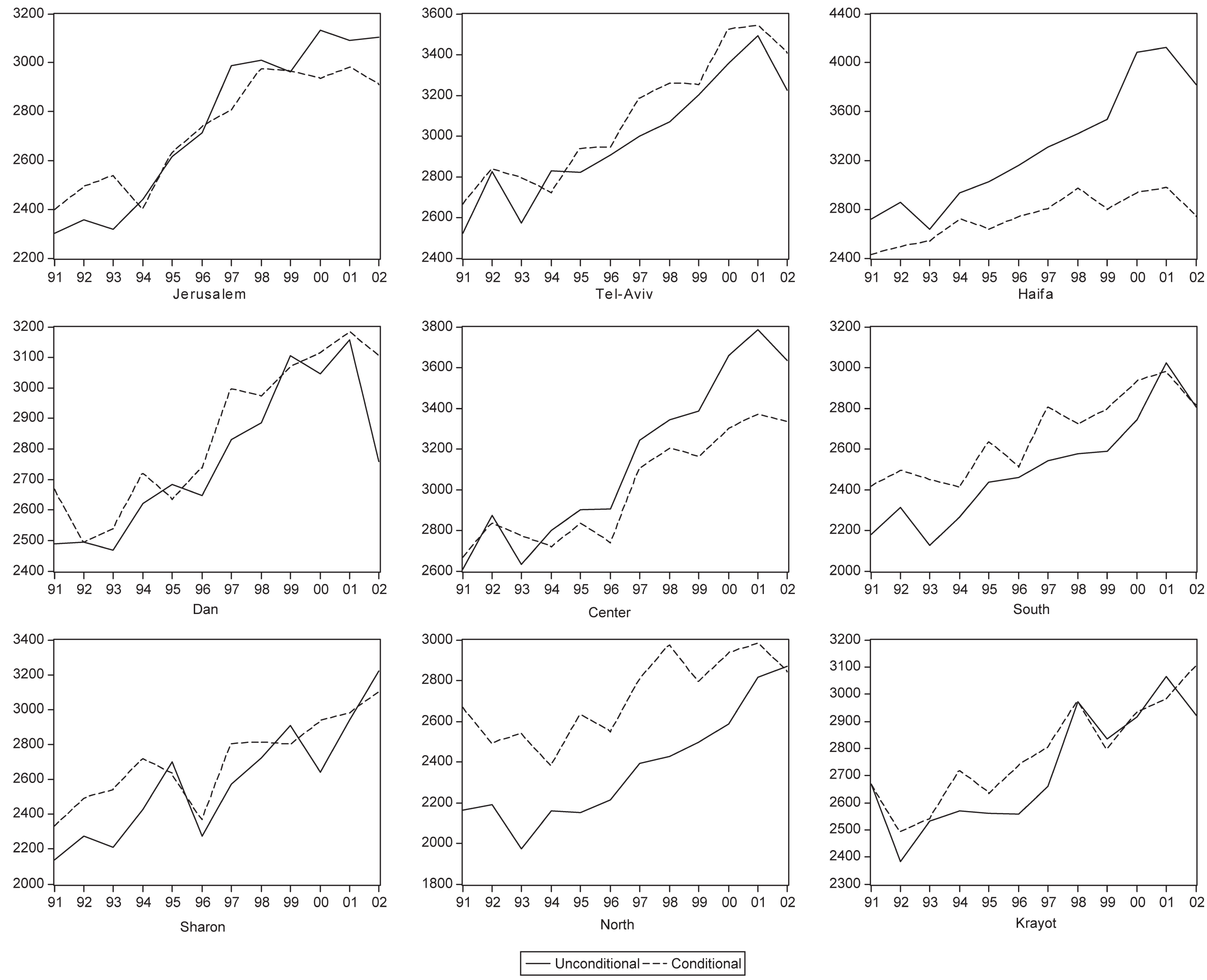

Fig. 2. Conditional and unconditional earnings, by region

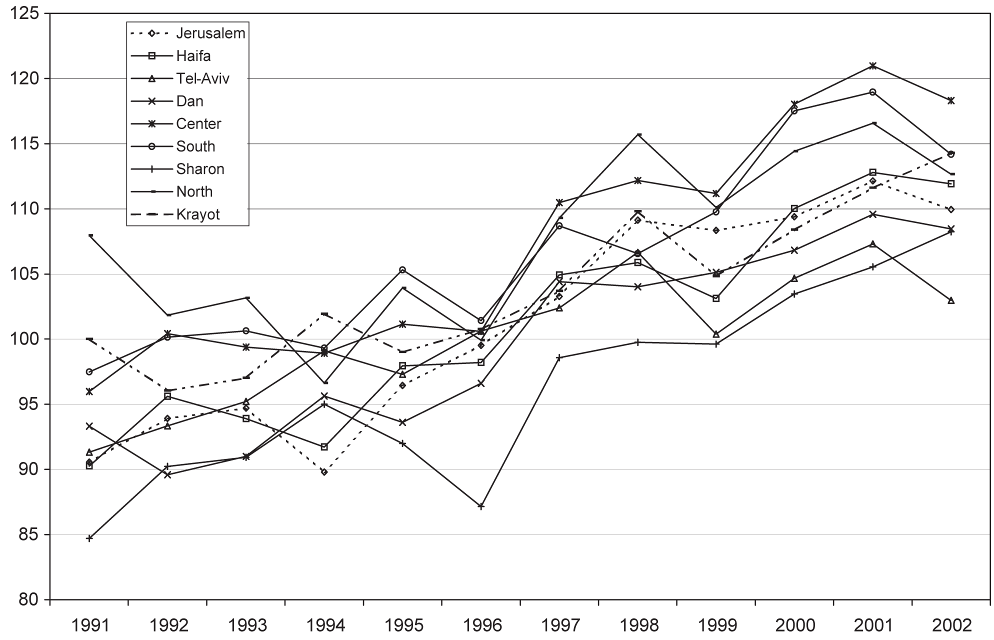

Fig. 3. Conditional earnings deflated by regional cost of living (COL) indices

comparing earnings between regions. Second, this is introduced into a comparison of regional differences in COLs.[14] This exercise reveals the importance of allowing for heterogeneity in COL differences when comparing real earnings between regions. Third, conditional and unconditional measures of 'sigma-convergence', both with and without accounting for COL heterogeneity, are compared. Strictly speaking, conditional and unconditional Gini-convergence are compared since Gini rather than the standard deviation is being used to measure regional inequality.

Fig. 2 compares conditional and unconditional real wages. The difference between them reflects two quite separate phenomena: the effect of the regional dummies (δ_{rt}) and the effect of the regional characteristics. Since the Krayot serve as the base region, the conditional and unconditional earnings in the base year (1991) are necessarily the same. Subsequently, the conditional earnings in the Krayot exceeded their unconditional counterparts because the conditioning variables in the Krayot changed adversely, i.e. to lower earnings. In the North and South conditional earnings systematically exceed unconditional earnings for two reasons. First, δ tends to be negative for these regions (Table 5), and, second, the characteristics are adverse. However, these effects lessen and the gap narrows. In other regions, such as Haifa and the Center, the opposite occurs, while in Jerusalem, Tel Aviv, and Dan the difference between conditional and unconditional earnings tends to be small.

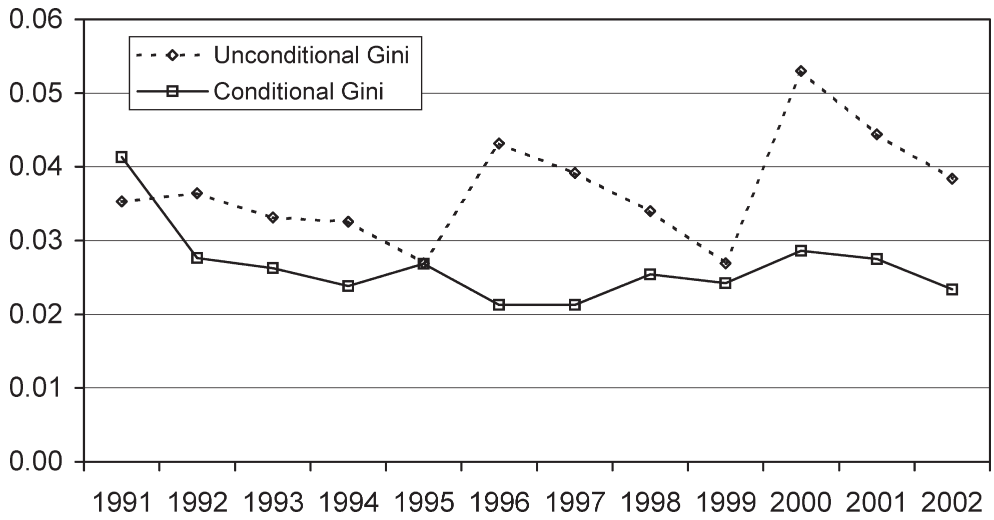

Fig. 4. Conditional and unconditional interregional Gini coefficients

Fig. 3 plots the data for conditional earnings presented in Fig. 2 deflated by regional COL indices. These COLs reflect regional differences in house price, services, and goods (BEENSTOCK and FELSENSTEIN, 2007). Whereas in Fig. 2 Tel Aviv has the highest conditional earnings, in Fig. 3 it does considerably less well because of its high COL. In contrast, the South is well placed in Fig. 3 and poorly placed in Fig. 2 because of its low COL.

The conditional and unconditional interregional Gini coefficients for COL-adjusted earnings are plotted in Fig. 4. The unconditional Gini coefficient rises over time indicating Gini divergence in regional wages. By contrast, the conditional Gini coefficient remains stable over time and is persistently smaller than its unconditional counterpart. By 2000 the unconditional Gini is almost twice its conditional counterpart, but the gap narrowed subsequently. The gap between the two reflects the contribution of regional characteristics to regional inequality. What remains is the regional inequality that is independent of these characteristics, i.e. the contribution of the regional dummy effects (δ_{rt}) and regional differences in COLs. Had δ_{rt} been zero and COLs been the same across regions, the Gini of conditional COL-adjusted earnings would have been zero.

REGIONAL MOBILITY AND BETA-CONVERGENCE

This section uses the results obtained above on conditional regional earnings for investigating beta-convergence. In doing so, the statistical methodology presented in the Methods section is used. First, beta is estimated over time both conditionally and unconditionally. This analysis sheds light on the degree of absolute mobility in the short, medium and longer runs, as well as on the effect of conditioning upon empirical measures of mean reversion. Second, the GMI is used to measure relative mobility. GMIs, both conditionally and unconditionally, are calculated over different time periods. This analysis also sheds light on the effect of conditioning upon measures of relative mobility, as well as on relative mobility in the short, medium and longer runs.

The section begins by discussing relative, or Gini, mobility. Fig. 5 plots GMI for conditional and unconditional COL-adjusted regional earnings. In the former case mobility is induced by two phenomena: the change in the regional dummies (Table 5) and the change in regional COLs. In the latter case it is additionally induced by changes in regional characteristics. Conditional mobility measures the underlying mobility. Had regional COLs and dummies remained unchanged conditional mobility is zero by definition, but unconditional mobility may have been positive because of changes in regional characteristics. In the authors' opinion the difference between these two measures of mobility is insightful.

The section begins by calculating Gini mobility between 1991 and 1992, and thereafter by calculating cumulative GMIs. Had regional characteristics been frozen at their base year (1991) level, the two schedules in Fig. 5 would have been identical by construction. The fact that there is more Gini mobility in unconditional earnings indicates that changes in regional socio-demographics on the whole induced greater mobility. It should be noted, however, that changes in regional socio-demographics can induce lower mobility, as was the case during 1991–94. The apparently high degree of mobility in unconditional earnings in fact concealed a low degree of inherent (conditional) regional mobility. Indeed, as much as half of the mobility in regional earnings is due to changing socio-demographics. This further emphasizes the importance of controlling for regional characteristics in measuring the dynamics of regional inequality.

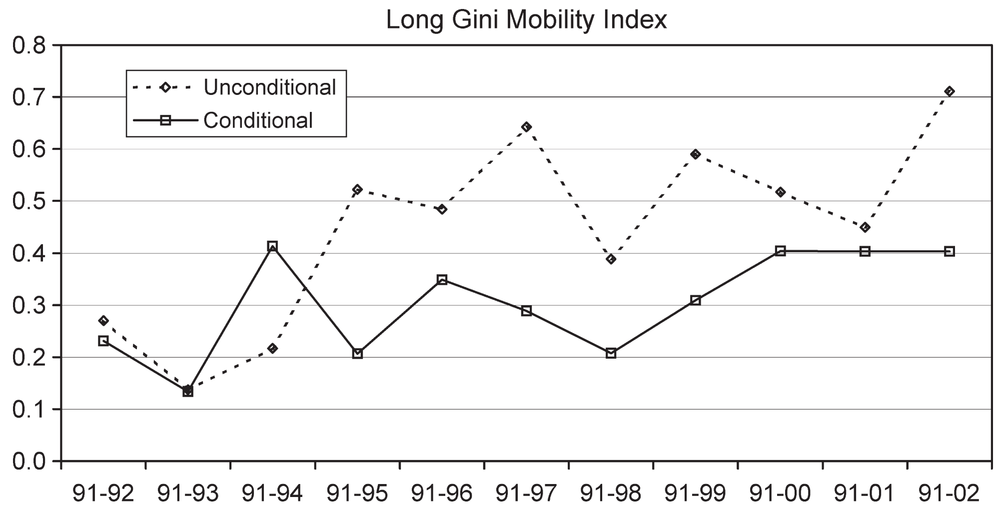

Fig. 5. Conditional and unconditional cumulative Gini Mobility Indices (GMIs)

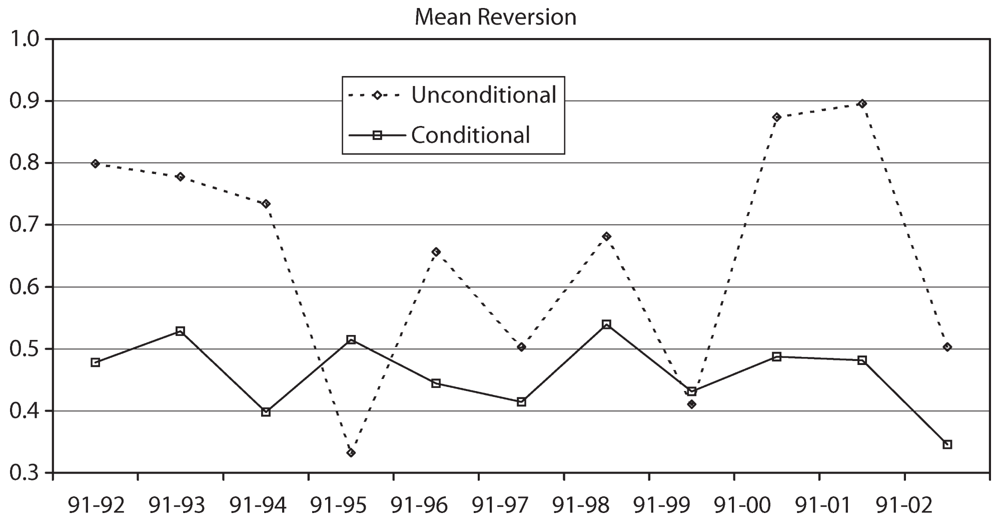

Fig. 6. Conditional and unconditional cumulative beta coefficients

Finally, conditional and unconditional quantity mobilities in regional COL-adjusted earnings are compared. Fig. 6 compares beta, or the mean reversion coefficient, for conditional and unconditional earnings cumulatively. It might be thought that, as in Fig. 5, where rank mobility increases cumulatively, the same would apply to quantity mobility. However, Fig. 6 shows that this does not apply to quantity mobility as measured by beta. Indeed, this is true for both types of earnings, conditional and unconditional. This shows that it is important to distinguish between the two types of mobility. In addition, according to Fig. 5, unconditional earnings are more rank-mobile that conditional earnings. Precisely the opposite applies to quantity mobility in Fig. 6, where beta for unconditional earnings is systematically larger than its counterpart for conditional earnings. Beta for conditional earnings is roughly half its counterpart for unconditional earnings, indicating a moderate degree of quantity mobility. By contrast, unconditional earnings indicate that there is little quantity mobility in regional earnings, although, as shown in Fig. 5, there is some degree of rank mobility. Beta for unconditional earnings ranges between 0.3 and 0.9 and is typically higher and more volatile than its conditional counterpart. Fig. 6 shows that conditional earnings are more immobile in quantity than unconditional earnings. This finding parallels that of Fig. 5 where conditional earnings were more immobile in rank. Again, it can be seen that accounting for regional characteristics can substantially change conclusions about the degree of mobility and inequality.

Note that cumulative beta can change quite sharply from one year to the next. For example, unconditional beta for 1991–95 is only half its counterpart for 1991–94. This in itself does not imply anything about beta mobility between 1994 and 1995. The reason for this is that one cannot infer cumulative correlations from correlations between consecutive years without additional information on the partial correlations between these consecutive years. This logic also lies behind the sharp increase in cumulative beta between 1991 and 2000.

CONCLUSIONS

This paper joins a growing literature that stresses the importance of accounting for regional heterogeneity in the dynamic analysis of regional economic disparities. In the standard literature regions are assumed to be homogeneous in that their socio-demographic composition is assumed to be broadly similar. It might be taken for granted that the law of large numbers implies that regions might be expected to be broadly homogeneous. However, the present paper has shown that in Israel there is a substantial degree of regional socio-demographic heterogeneity.

It has been shown that this regional heterogeneity accounts for a large component of regional wage differentials. Similar findings have been reported for the UK (Duranton and Monastiriotis, 2002) and Brazil (Azzoni and Servo, 2002), which suggests that regional heterogeneity is important in large countries as well as small ones such as Israel. Controlling for socio-demographic diversity radically reduces measures of regional inequality, which implies that most of the observed regional inequality is not inherent, but due to regional diversity. For example, if workers in a region happen to be young and less educated, or if there is a predominance of subpopulations with poor pay, earnings will be lower not because of regional factors, but due to these characteristics.

The regional convergence literature has typically ignored socio-demographic heterogeneity. The present paper argues that tests for regional convergence should be carried out by conditioning upon socio-demographic attributes of the regions. In this, the proposal has much in common with conditional convergence in the international growth convergence literature. The results show that conditional earnings Gini-converge by more than do unconditional earnings across regions. This shows that tests for convergence are sensitive to conditioning. Whereas DURANTON and MONASTIRIOTIS (2002) investigated convergence in the individual returns to attributes, such as education, the present paper has broken new ground by using a model to test for convergence by conditioning jointly upon all of these attributes. In doing so, this paper has taken account of regional COL differentials to which economic geographers and regional scientists attach growing importance.

Apart from focusing upon Gini-convergence, the paper has also investigated the effects of conditioning on beta-convergence. Here too one finds that conditioning serves to alter the results. Attention is drawn to differentiating between beta-convergence, which measures absolute mobility, and measures of mobility that stress rank or relative mobility. The recently developed Gini mobility index is used to measure rank mobility both conditionally and unconditionally. Here too it is found that conditioning makes a large difference to the results; conditional Gini mobility turns out to be only half its unconditional counterpart. Interestingly, it turns out that the two measures of mobility, rank and quantity, behave quite differently. First, there is more quantity mobility than rank mobility in conditional earnings. Second, the trend in rank mobility is positive, whereas there is no discernible trend in quantity mobility. It is suggested that the distinction between the two concepts of mobility enriches the understanding of the dynamics of regional disparities.

The results further suggest that in the case of Israel a dichotomous core–periphery regional structure might more adequately describe regional dynamics than a more disaggregated structure (such as the nine-region classification used herein). In contrast to findings from larger countries where regional dummies have a significant effect on earnings (e.g. DURANTON and MONASTIRIOTIS, 2002), in the present case the only regions that report consistently significant effects over the whole period are the core regions (Tel Aviv and the Central region). This suggests that once one controls for socio-demographic heterogeneity, Israel is primarily a two-region country and that all other regional subdivisions outside this core–periphery structure are not really relevant. The authors do not know whether this dichotomy stems from the smallness of Israel or if the same would apply intra-regionally in larger countries. After all, a typical region in the UK or Brazil is of similar size to Israel.

However, once COL differentials are taken into consideration, this core–periphery dichotomy is moderated. For example, Tel Aviv, which leads the regional rankings in terms of unconditional earnings, drops considerably after conditioning and COL adjustment. The latter largely reflects the high price of housing in Tel Aviv. In addition, the peripheral North and South jump up the rankings largely due to cheap housing in those areas.

Conditioning for socio-demographics reveals the bare bones of regional structure. The paper does not explain why conditional regional earnings differ. Amenity theory would explain them in terms of compensating differentials. If this were true, the high price of housing in Tel Aviv would reflect the regions' concentration of amenities, and the low price of housing in the North and South would reflect the dearth of amenities in these regions. The New Economic Geography offers a complementary interpretation by stressing increasing returns to scale in production and consumption, and by predicting that earnings will be higher in regions where scale is larger. Indeed, in the case of Israel, earnings are higher in the centre, where scale is higher, and lower in the periphery, where scale is lower.

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NOTES

1. DURANTON and MONASTIRIOTIS (2002) and HENLEY (2005) for the UK; AZZONI and SERVO (2002) for Brazil; and COMBES *et al.* (2007) for France.
2. DICKIE and GERKING (1987, 1998) concluded that US regional wage differentials in 1976 disappeared after conditioning, and provincial wage differentials in Canada in 1988–89 were reduced by 40%. MAIER and WEISS (1986) showed that regional wage differentials in Austria persisted even after conditioning on regional demographic characteristics.
3. Several studies use regional deflators but do not condition earnings (e.g. DUMOND *et al.*, 1999; JOHNSTON *et al.*, 1996; DELLER *et al.*, 1996; EBERTS and SCHWEITZER, 1994).
4. Arabs from East Jerusalem are excluded from the Household Income Survey.
5. Although there are only nine regions, 12 time periods contribute to the effective number of degrees of freedom. Analogous to the panel DW statistic for autocorrelation, a panel Moran's I statistic has been estimated. The panel DW statistic is meaningful when the number of time periods is nine and the number of cross-section units is 12. In the present case, the number of cross sections is nine and the number of time periods is 12. Unfortunately, there is as yet no formal definition of the panel Moran's I statistic.
6. Using macrodata, as in HENLEY (2005), induces bias in non-linear models, e.g. the mean of $\ln X_i$ does not equal the log of the mean.
7. DURANTON and MONASTIRIOTIS (2002) allow the β's to vary by region. The present paper tests the restriction that $\beta_i = \beta$.

8. DURANTON and MONASTIRIOTIS (2002, p. 226) suggested occupation as such an instrument. However, occupation will tend to affect earnings.
9. Restrictions of space prevent the present paper from reporting the full set of estimates of equation (1) for each year. However, a complete set of Mincer equations for 1991–2002 is available from the authors on request.
10. As in note 5, a panel Moran's *I* statistic is also calculated for average Mincer residuals for each year of estimation (1991–2002). In only four of these years is the Moran's *I* statistic significant at $p < 0.05$.
11. In DURANTON and MONASTIRIOTIS (2002) the same phenomenon occurs but even more acutely.
12. Since robust standard errors are larger than regular standard errors, some regional dummies become marginally insignificant.
13. Using Stata's Treatreg procedure.
14. A simple method for proxying regional COLs is applied in BEENSTOCK and FELSENSTEIN (2007).

REFERENCES

AZZONI C. R. and SERVO L. M. S. (2002) Education, cost of living and regional wage inequality in Brazil, *Papers in Regional Science* **81**, 157–175.

BARRO R. J. and SALA-I-MARTIN X. (1991) Convergence across states and regions, *Brookings Papers in Economic Activity* **1**, 107–182.

BEENSTOCK M. and FELSENSTEIN D. (2007) Mobility and mean reversion in the dynamics of regional inequality, *International Regional Science Review* **30**, 335–361.

BERMAN E. (2000) Sect, subsidy and sacrifice: an economist's view of ultra-orthodox Jews, *Quarterly Journal of Economics* **115**, 905–953.

CHISWICK B. (1998) Hebrew language usage: determinants and effects on earnings among immigrants in Israel, *Journal of Population Economics* **11**, 253–271.

COMBES P.-P., DURANTON G. and GOBILLON L. (2007) Spatial wage disparities: sorting matters, *Journal of Urban Economics* (forthcoming) .

CUADRADO-ROURA J. R., GARCIA-GRECIANO B. and RAYMOND J. L. (1999) Regional convergence in productivity and productive structure: the Spanish case, *International Regional Science Review* **22**, 35–53.

DELLER S., SHIELDS M. and TOMBERLIN D. (1996) Price differentials and trends in state income levels: a research note, *Review of Regional Studies* **26**, 99–113.

DICKIE M. and GERKING S. (1987) Interregional wage differentials: an equilibrium perspective, *Journal of Regional Science* **27**, 571–585.

DICKIE M. and GERKING S. (1998) Interregional wage disparities relocation costs and labor mobility in Canada, *Journal of Regional Science* **38**, 61–87.

DUMOND J. M., HIRSCH B. T. and MACPHERSON D. A. (1999) Wage differentials across labor markets and workers: does cost of living matter?, *Economic Inquiry* **37**, 577–598.

DURANTON G. and MONASTIRIOTIS V. (2002) Mind the gaps: the evolution of regional earnings inequalities in the UK, 1982–1997, *Journal of Regional Science* **42**, 219–256.

EBERTS R. W. and SCHWEITZER M. E. (1994) Regional wage convergence and divergence: adjusting wages for cost of living differences, *Economic Review, Federal Reserve Bank of Cleveland* **39**, 26–37.

HECKMAN J. A. (1979) Sample selection bias as a specification error, *Econometrica* **47**, 153–161.

HEDGES L. V. and OLKIN I. (1985) *Statistical Methods for Meta-analysis*. Academic Press, New York, NY.

HENLEY A. (2005) On regional growth convergence in Great Britain, *Regional Studies* **39**, 1245–1260.

JOHNSTON R., MCKINNEY M. and STARK T. (1996) Regional price level variations and real household incomes in the United Kingdom, *Regional Studies* **30**, 567–578.

JUHN C., MURPHY K. M. and PIERCE B. (1993) Wage inequality and the rise in returns to skill, *Journal of Political Economy* **101**, 410–442.

MAIER G. and WEISS P. (1986) The importance of regional factors in the determination of earnings: the case of Austria, *International Regional Science Review* **10**, 211–220.

PORTNOV B. A. and ERELL E. (2003) *Inter-Regional Disparities in Israel: Data from the Census of Population and Housing, 1948–1995*. Research Report No. 2. Central Bureau of Statistics, Jerusalem.

SCHECHTMAN E. and YITZHAKI S. (1987) A measure of association based on Gini's mean difference, *Communications in Statistics Theory and Methods* **A16**, 207–231.

SUMMERS R. and HESTON A. (1991) The Penn World Table (Mark 5): an expanded set of international comparisons, *Quarterly Journal of Economics* **106**, 327–368.

TSIONAS E. G. (2000) Regional growth and convergence: evidence from the United States, *Regional Studies* **34**, 231–238.

YITZHAKI S. (2003) Gini's mean difference: a superior measure of variability for non-normal distributions, *Metron* **61**, 285–316.

YITZHAKI S. and WODON Q. (2004) Mobility, inequality and horizontal equity, *Research on Economic Inequality* **12**, 177–198.