Regional Heterogeneity and Conditional Convergence

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Abstract

This paper stresses the importance of accounting for regional heterogeneity in the dynamic analysis of regional economic disparities. Studies of regional growth invariably presume regions are homogeneous in that their socio-demographic composition is assumed to be broadly similar. We argue that any 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, we estimate various measures of conditional regional earnings inequality using Israeli regional data for the period 1991 – 2002. Our results show that much of the regional earnings inequality may be accounted for by the conditioning variables. Both in measures of regional convergence and regional mobility, conditioning makes a large difference to the results accounting for up to half the observed levels of inequality. Ignoring regional heterogeneity may therefore lead to serious over-estimation of the underlying level of regional inequality.

Keywords: regional homogeneity, inequality, conditional convergence, mobility

JEL Classification: D63, O18, R12

1. Introduction

The empirical literature on regional growth convergence has implicitly assumed that the labor force is, on average, homogeneous between regions (Barro and Sala-I-Martin 1995, Tsionas 2000, Cuadrado-Roura et al 1999, Le Gallo and Ertur 2003 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. Regional homogeneity implies that wages in different regions should converge upon some common value. Suppose, however, that the labor 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 inter-regionally. 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.

Two recent studies (Duranton and Monastiriotis 2002 for the UK and Azzoni and Servo 2002 for Brazil) 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[1]. They also attach importance to regional differences in the cost of living, which as noted by Beenstock and Felsenstein (2004), have also been typically ignored in the empirical literature, and which reduce measured regional inequality. A related paper is by Dumond, Hirsch and Macpherson (1999), who measure conditional regional wage

[1] Dickie and Gerking (1987, 1998) conclude that US regional wage differentials in 1976 disappear after conditioning, and provincial wage differentials in Canada in 1988-9 are reduced by 40%. Maier and Weiss (1986) show that regional wage differentials in Austria persist even after conditioning on regional demographic characteristics.

inequality in the US during 1985 – 1995 allowing for regional differences in living costs. However, they estimate average inequality over the period without investigating how conditional inequality has evolved over time.

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. Also, tests of regional convergence that ignore these differences may generate quite different results to tests that condition upon these regional differences.

In this paper we use data for Israel during 1991 – 2002 to estimate various measures of conditional regional wage inequality. We show that much of the regional inequality in earnings in Israel may be accounted for by the conditioning variables. Indeed, whereas there is regional sigma-divergence in unconditional wages, conditional wages display regional sigma stability. This evidence shows that ignoring regional heterogeneity may not only lead to serious over-estimation of the underlying level of regional inequality, but it may also lead to erroneous conclusions regarding its trend, or regional sigma convergence. We also show that while there is greater regional mobility in unconditional earnings, this conceals a low degree of inherent regional mobility. Our results show that up to half the mobility in regional earnings comes from socio-demographic characteristics. This serves to underscore the importance of conditioning for these attributes when looking at inequalities.

Our results therefore 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 United Kingdom, 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. We also show that it is important to take account of cost-of-living differentials in the empirical analysis of regional convergence.

2 Regional Heterogeneity in Israel

Portnov and Erell (2003) have shown 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, labor 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 here come from the Household Income Survey (HIS) conducted annually by the Central Bureau of Statistics (CBS), covering roughly 13,000 respondents. Table1 shows that in 1995 the average age of earners was 40.19 years in Haifa and only 35.04 years in the North (see Map1). 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-Jews[2].

Map1 here

Table1 here

Average monthly earnings varied substantially between the regions; there is a 40 percent 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. In this paper we examine whether these regional differences in earnings still persist after conditioning on the socio-demographics of the regions.

3. Methodology

To estimate conditional differences in regional earnings we estimate "Mincer models" in which the labels i, r and t refer to the individual, the region in

[2]Arabs from East Jerusalem are excluded from the Household Income Survey.

which he lives, and the year of observation respectively, and X is a vector of socio-demographic controls:

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

$D_{ri} = 1$ if individual i lives in region r and zero otherwise, and ε_{it} denotes the residual error with variance σ^2_t. In the absence of panel data for individuals, equation (1) is 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 may vary over time. We follow Azzoni and Servo (2002) and Maier and Weiss (1986) in assuming that the β's do not vary by region[3]. 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. i) It varies directly with the change in α, which captures the national trend in wage growth, and ii) 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. iii) Expected wage growth depends upon the regional change in these characteristics, e.g. the level of education in the region increases, and iv) it varies directly with the change in δ_r, which captures the change in return to living in region r. Finally, v) if the unexplained variance of earnings increases expected wage growth will be larger. In short, equation (2) may be used to decompose regional earnings growth into these 5 components.

Having estimated equation (1) its parameters may be substituted into equation (2). Several applications of equation (2) are suggested. The first is to calculate the basic return to earning in region r in time t. It is equal to $\alpha_t + \delta_{rt}$. We refer to this as the basic regional wage, which deducts from regional earnings growth components ii

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[3] Duranton and Monastiriotis (2002) allow the β's to vary by region.

and iii. The second is the conditional regional wage, which is equal to $\alpha_t + \delta_{rt} + X_0\beta_t$, where X_0 denotes 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, Murphy and Pierce (1993) we may use the Mincer model to distinguish between within and between-group inequality in log earnings. Within-group inequality is measured by the estimate of σ^2_t, 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.

We use the Household Income Survey (HIS) to estimate equation (1). Following Beenstock and Felsenstein (2004) we divide Israel into 9 regions that are illustrated on Map1. Since the necessary regional data are only available since 1991 we carry out the analysis for the years 1991 – 2002. The X variables include age and its square, years of schooling, 7 occupational dummies, 8 economic sectoral dummies, 9 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 labor economists in Israel. The base region is the Krayot, which is a group of towns near Haifa.

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 potentially endogenous too. This means that separate instrumental variables are required for each of these potentially endogenous variables. For example, in the case of the regional dummies we would require variables which affect choice of residence without directly affecting earnings[4], 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. This means that the parameter estimates of equation (1) could be inconsistent, in which case conditional regional differences may be over or under-stated.

The fact that place of residence is endogenous does not automatically mean that estimates of δ_r must be inconsistent. If inhabitants in region r are positively/negatively self-selected then δ_r will be over/under - estimated. 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. If, however, they are neutrally selected then δ_r will be consistent. Neutral selection occurs when unobserved heterogeneity in earnings (ε in equation (1)) is independent of unobserved heterogeneity in selection. We assume neutral selection by default.

4. Mincer Models 1991 - 2002

In Table 2 we report an illustrative estimate of equation (1) for 1995. Space prevents reporting the full set of estimates of equation (1) for each year. Nevertheless, in Table 3 we report estimates of some key β 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 1991-7 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 inequality. Overall earnings inequality has remained broadly

[4] Duranton and Monastiriotis (2002, p 226) suggest occupation as such an instrument. However, occupation will tend to affect earnings.

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 2 here

Table 3 here

In Table 4 we report the full set of δ 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[5]. 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. 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 but generally insignificant.

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 we suggest two separate statistical tests. In the first, we re-estimate the Mincer model for year t with zero restrictions on regional dummy variables ($\delta_{rt} = 0$ given t), and use an F-test to retain the regional dummy coefficients that are statistically significant. In the second, we use the results presented in Table 4 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). We use the inverse chi-square meta-statistic (Hedges and Olkin 1985):

[5] In Duranton and Monastiriotis (2002) the same phenomenon occurs but even more acutely.

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

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

In Table 5 we report the estimates of these regional dummy variable coefficients that survive the F- tests mentioned above. In Tel Aviv earnings are between 9 to 18 percent higher than in the base regions, while in the South they are about 3 to 12 percent lower.

Table 4 here

Table 5 here

5. Conditional Regional Inequality

In Figure 1 we compare 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.

Figure 1 here

In Figure 2 we plot the data for conditional earnings presented in Figure 1 deflated by regional cost of living (COL) indices. These COLs reflect regional differences in house price, services and goods (Beenstock and Felsenstein 2004).

Whereas in Figure 1 Tel Aviv has the highest conditional earnings, in Figure 2 Tel Aviv does considerably less well because of its high cost of living. In contrast, the South is well-placed in Figure 2 and poorly placed in Figure 1 because of its low cost of living.

Figure 2 here

The conditional and unconditional inter-regional Gini coefficients for COL adjusted earnings are plotted in Figure 3. 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 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.

Figure 3 here

6. Regional Mobility

As in Beenstock and Felsenstein (2004) we distinguish between rank and quantity mobility (sometimes referred to as relative and absolute mobility). The former focuses on changes in the rank of region r in the distribution, while the latter focuses upon the level of earnings. These two types of mobility may or may not move in tandem. A region's earnings may increase relative to the national average, in which case earnings are upwardly mobile in quantity, while at the same time the region's rank in the distribution falls, in which case there is downward mobility in rank.

Since we use Gini as a measure of inequality, and we wish to relate mobility to inequality, we estimate beta from a Gini regression of Y_{rt} on Y_{rt-1}. It is defined as:

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

where $R_{rt} = F(Y_{rt})$ is the rank of Y_{rt} over *n* in ascending order[6].

Following Schechtman and Yitzhaki (1987) Gini may be defined as:

$$G_t = \frac{2\,\mathrm{cov}(Y_{rt}, R_{rt})}{\overline{Y}_t} \qquad (4)$$

where G_t is the Gini coefficient measuring inequality in Y between *n* regions at time t. The Gini correlation between Y in period t and income rank in period t-1 is defined as:

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

and is bounded between 1 and –1. It measures the degree of (backward) rank-mobility. Y is perfectly rank-immobile when $\Gamma = 1$. If $\Gamma = 0$ there is random rank-mobility because it is not possible to infer R_{rt-1} using information on Y_{rt}. For all practical purposes this represents the case of complete mobility. When $\Gamma = -1$ there is perfectly perverse mobility: the richest swaps rank with the poorest, the second most rich with the second most poor, and so on.

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

$$\beta_t = \Gamma_{t.t-1} \frac{G_t}{G_{t-1}} \frac{\overline{Y}_t}{\overline{Y}_{t-1}} \qquad (6)$$

Equation (6) shows that beta, which measures quantity-immobility, depends upon three factors. It varies directly with the degree of (backward) rank-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 leveling-up as measured by $\overline{Y}_t / \overline{Y}_{t-1}$, which exceeds unity in the event of leveling-up and is less than unity in the event of leveling down. If all three components happen to equal unity, then $\beta = 1$ and the rate of mean reversion is zero. When $G_t = G_{t-1}$ and $\overline{Y}_t = \overline{Y}_{t-1}$, equation (6) implies that $\beta = \Gamma$, i.e. rank-mobility and quantity-mobility are identical. 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

[6] OLS uses Y_{rt-1} instead of R_{rt-1}. Since the rank of Y is measured better than Y itself, the Gini estimator may be regarded as an EV (errors-in-variables) estimator.

and leveling. 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 rank - mobility differ, unless Y_{rt-1} and Y_{rt} happen to be exchangeable[7]. The problem is similar to the common index number effect, where for example, the rate of inflation depends upon the direction of measurement. Yitzhaki and Wodon (2004) have suggested a symmetric Gini mobility index, which weights the forward and backward measures of mobility, defined as:

$$S_t = \frac{G_{t-1}(1-\Gamma_{t-1.t}) + G_t(1-\Gamma_{t.t-1})}{G_{t-1}+G_t} \qquad (7)$$

S is naturally bounded between 0 (no mobility) and 2 (perfectly perverse mobility). When S = 1 mobility is random. Note that if Y_{it} and Y_{it-1} are exchangeable $\Gamma_{t-1.t} = \Gamma_{t.t-1} = \Gamma_t$ in which case $S_t = 1 - \Gamma_t$. Note also that this measure of mobility does not require arbitrary definitions of mobility matrices in which intra-decile mobility is given zero weight.

In Figure 4 we plot Gini mobility indices 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 our opinion the difference between these two measures of mobility is insightful.

We begin by calculating Gini mobility between 1991 and 1992, and thereafter calculate cumulative Gini mobility indices. Had regional characteristics been frozen at their base-year (1991) level the two schedules in Figure 4 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

[7] Exchangeability means that the shapes of the marginal distributions of Y_t and Y_{t-1} are similar.

can induce lower mobility, as was the case during 1991 – 4. The apparently high degree of mobility in unconditional earnings in fact concealed a low degree of inherent (conditional) regional mobility. In fact, 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.

Figure 4 here

Finally, we compare conditional and unconditional quantity mobility in regional COL adjusted earnings. Figure 5 compares beta, or the mean reversion coefficient, for conditional and unconditional earnings cumulatively. One might think that as in Figure 4, where rank mobility increases cumulatively, the same would apply to quantity mobility. However, Figure 5 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. Also, according to Figure 4 unconditional earnings are more rank-mobile that conditional earnings. Precisely the opposite applies to quantity-mobility in Figure 5, 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 Figure 4 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. Figure 5 shows that conditional earnings are more immobile in quantity than unconditional earnings. This finding parallels that of Figure 4 where conditional earnings were more immobile in rank. Once again we see 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 1991-5 is only half its counterpart for 1991-4. This in itself does not imply anything about beta-mobility between 1994-5. 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 – 2000.

Figure 5 here

7. 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, we have shown that in Israel there is a substantial degree of regional socio-demographic heterogeneity.

We have 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 observed regional inequality is not inherent, but is 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. We argue in this paper that tests for regional convergence should be carried out by conditioning upon socio-demographic attributes of the regions. In this, our proposal has much in common with conditional convergence in the international growth convergence literature. Our 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, we have broken new ground by using our model to test for convergence by conditioning jointly upon all of these attributes. In doing so we have taken account of regional cost-of-living differentials, to which economic geographers and regional scientists attach growing importance.

Apart from focusing upon Gini-convergence we have also investigated the effects of conditioning on beta convergence. Here too we find that conditioning serves to alter the results. We draw attention to differentiating between beta convergence, which measures quantity or absolute mobility, and measures of mobility that stress rank or relative mobility. We use the recently developed Gini mobility index to measure rank mobility both conditionally and unconditionally. Here too we find 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. Secondly, the trend in rank mobility is positive, whereas there is no discernable trend in quantity mobility. We suggest that the distinction between the two concepts of mobility enrich the understanding of the dynamics of regional disparities.

The results further suggest, that in the case of Israel a dichotomous core-periphery regional structure may more adequately describe regional dynamics than a more disaggregated structure (such as the 9-region classification used here). In contrast to findings from larger countries where regional dummies have a significant effect on earnings (for example, Duranton and Monastiriotis 2002) in our case, the only regions to report consistently significant effects over the whole period are the core regions (Tel Aviv and the Central region). This suggests that once we control for socio-demographic heterogeneity, Israel is primarily a 2-region country and that all other regional subdivisions outside this core-periphery structure are not really relevant. We do not know whether this dichotomy stems from the smallness of Israel or whether 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 cost-of-living 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. Also, the peripheral North and South jump up the rankings, largely due to cheap housing there.

Conditioning for socio-demographics reveals the bare bones of regional structure. We do 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 predicting that earnings will be higher in regions where scale is larger. Indeed, in the case of Israel earnings are higher in the center, where scale is higher, and lower in the periphery, where scale is lower.

It seems to us therefore that regional earnings data are consistent with the New Economic Geography, and amenity theory explains why despite this, COL-adjusted earnings are higher in the periphery than in the center. The crucial equilibrating agent seems to be house prices.

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Table 1: The Effect of Socio-Demographic Attributes on Regional Earnings Differences

	Age	Years of Schooling	Percent Non-Jewish	Percent Women in Lab. Force	Average Monthly Earnings (NIS)[2]
JERUSALEM	36.67	14.16	1.06%	53.32%	4012
North	35.04	11.31	49.05%	35.77%	3296
Haifa	40.19	13.21	8.95%	47.59%	4207
Sharon	37.55	12.48	13.29%	44.19%	4142
Center	38.47	13.07	3.15%	48.69%	4448
Tel Aviv	37.47	13.15	3.58%	48.79%	4633
Dan	38.66	12.81	1.16%	48.39%	4112
South	37.79	12.41	4.63%	47.74%	3734
Average[1]	37.67	12.73	11.98%	46.41%	

1. All variable averages are non-weighted and represent averages for the data set.

2. Estimated on basis of wage equation in Table 2.

Table 2: Illustrative Wage Regression

The earnings model is:

$\ln Y_k\,(i,t) = \alpha + \beta_1(i,t)AGE_k + + \beta_2(i,t)AGE^2_k + \beta_3(i,t)EDU_k + \beta_4(i,t)NONJ_k + \beta_5(i,t)MAR_k + \beta_6(i,t)MALE_k + \beta_7(i,t)SCHOOL_k + \beta_8(i,t)BR^*_k + \beta_9(i,t)OCC^*_k + \beta_{10}(i,t)REG^*_k + \varepsilon_k\,(i,t)$

Where $LnY_k\,(i,t)$ = log earnings for individual k in region i in time t;

- AGE = age of earner between 25-65;
- EDU = years of schooling;
- NONJ is coded as unity for non-Jewish earners;
- MAR is coded as unity for married earners;
- MALE is coded as unity for male earners;
- SCHOOL is coded as unity if last place of education is a talmudic academy (Yeshiva);
- BR* represents a series of eight sector dummies that are coded as unity if the branch is agriculture (BR1), industry (BR2), electricity and water (BR3), construction (BR4), commerce restaurants and hotels (BR5), transport and communications (BR6), finance and business services (BR7), public and community services (BR8);
- OCC* represents a series of seven sector dummies that are coded as unity if the occupation is scientific and academic professional (OCC1), other professionals and technicians (OCC2), managers (OCC3), clerks (OCC4), sales and service agents (OCC5), farm workers (OCC6), skilled industrial workers (OCC7),
- REG* represents a series of regional dummies that are coded as unity if the region is Jerusalem (REG1), Tel Aviv (REG2), Haifa (REG3), Dan (REG4), Center (REG5), South (REG6), Sharon (REG7), North (REG8).

The estimated equation for 1995 is:

Ln(earnings) = 5.025 + 0.074Age – 0.00076 Agesquare + 0.0694 Years schooling – 0.0641 Non-Jew + 0.5527 Male + 0.1846Married – 0.9729Ultra-Orthodox + 0.088Jerusalem +0.1983 Tel Aviv + 0.412 Haifa + 0.1241Dan + 0.1446Center – 0.0422South + 0.08491Sharon + 0.0555North

Source: Household Incomes Survey 1995, Central Bureau of Statistics.

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*	0.085*	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-Jews	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
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

* Significant < 0.001

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)
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

Standard figures in parentheses.

* Significiant < 0.05

Table 5: Regional Dummy Coefficients for Reduced Model

	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
Jerusalem	-0.106			-0.124					0.058			-0.063
Tel-Aviv		0.129	0.096		0.110	0.073	0.127	0.092	0.151	0.183	0.173	0.093
Haifa	-0.094											-0.125
Dan							0.066		0.093	0.060	0.065	
Center		0.129	0.089		0.074		0.100	0.074	0.123	0.117	0.123	0.071
South	-0.099		-0.036	-0.121		-0.087		-0.089				-0.096
Sharon	-0.134					-0.144		-0.056				
North				-0.130		-0.071						-0.088
Krayot												

Figure 1: Conditional and Unconditional Earnings, by Region

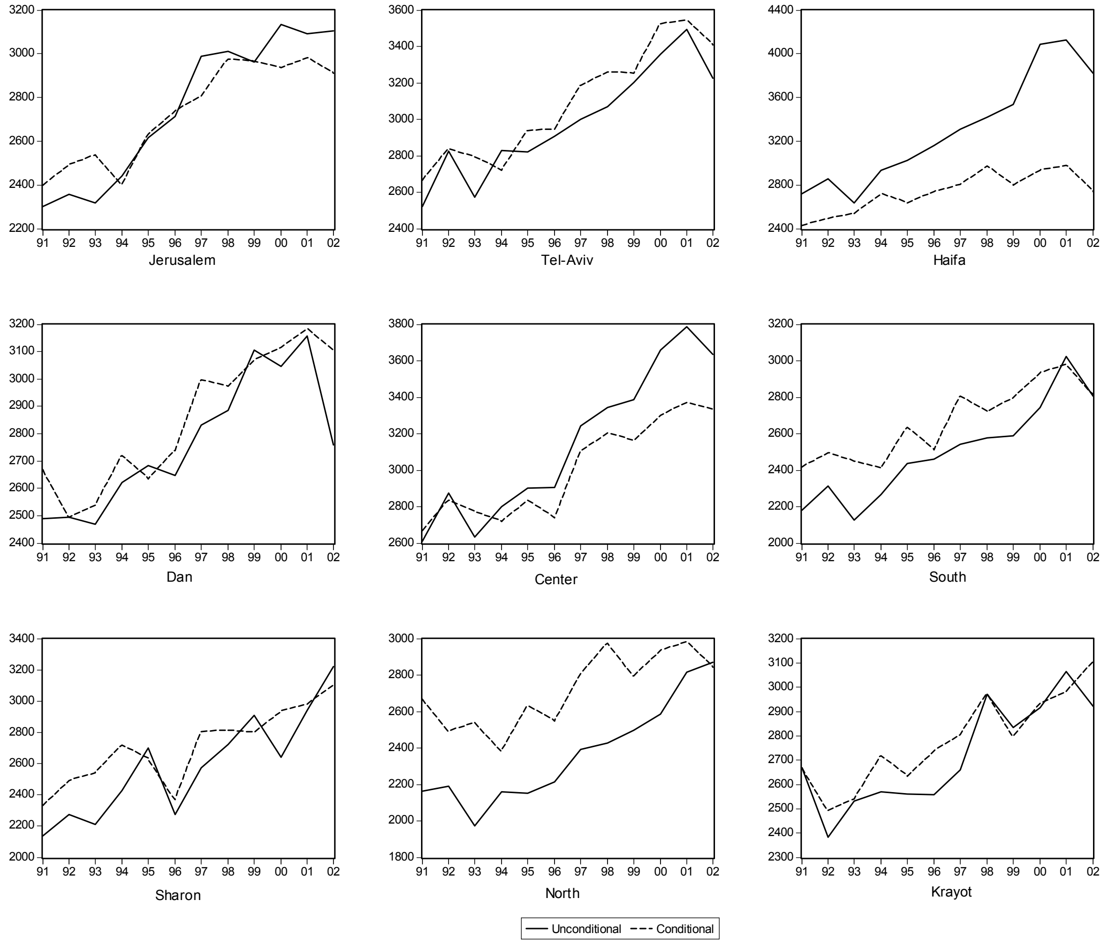


Figure 2: Conditional Earnings Deflated by Regional Cost of Living (COL) Indices

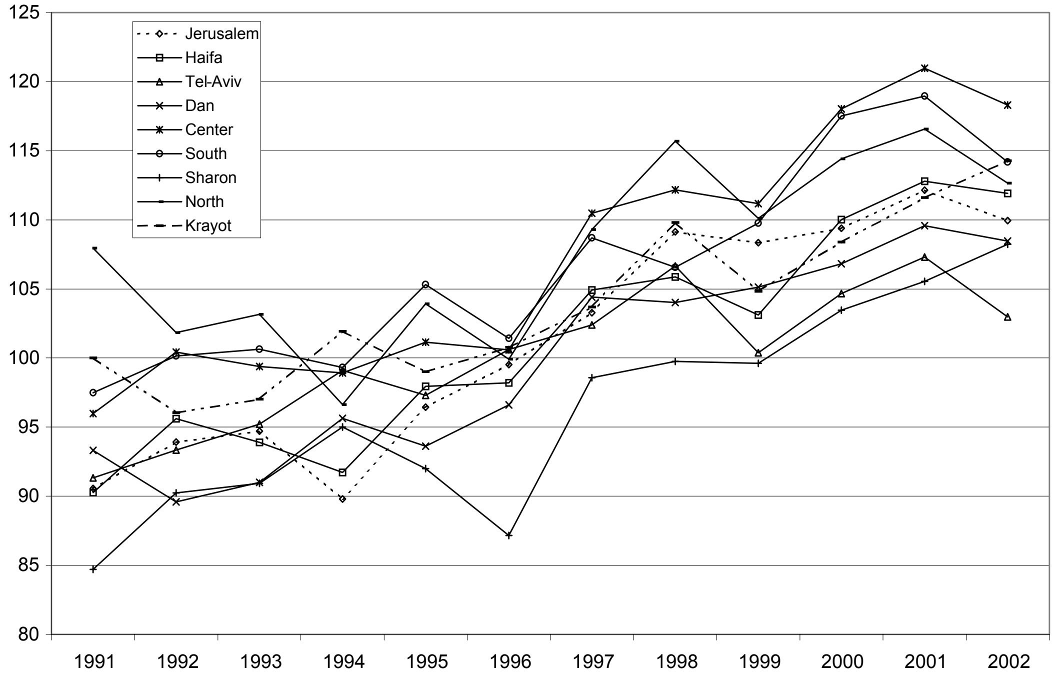


Figure 3: Conditional and Unconditional Inter-Regional Gini Coefficients

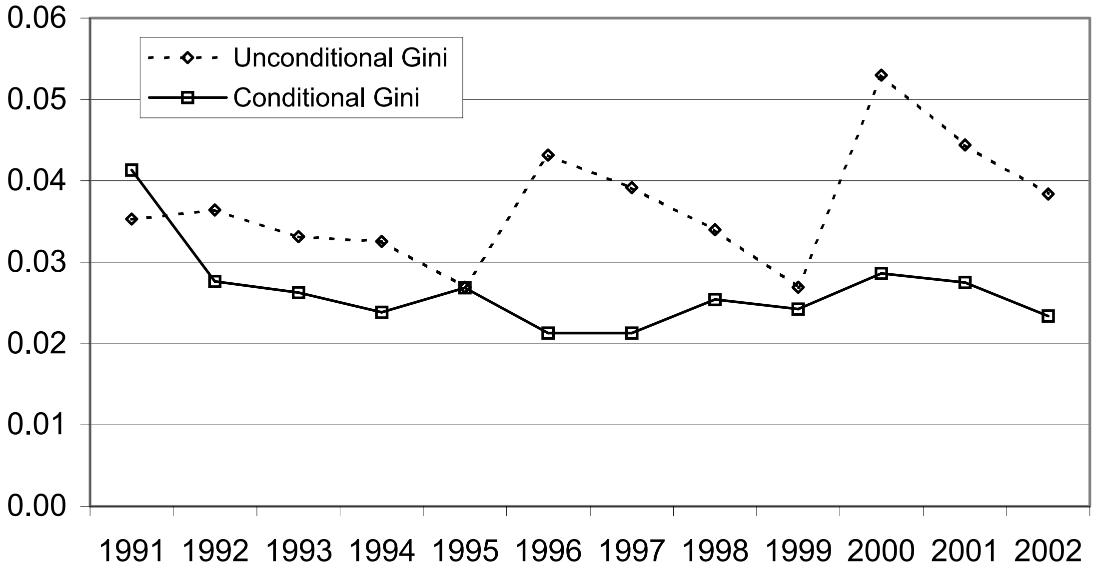


Figure 4: Conditional and Unconditional Cumulative Gini mobility Indices

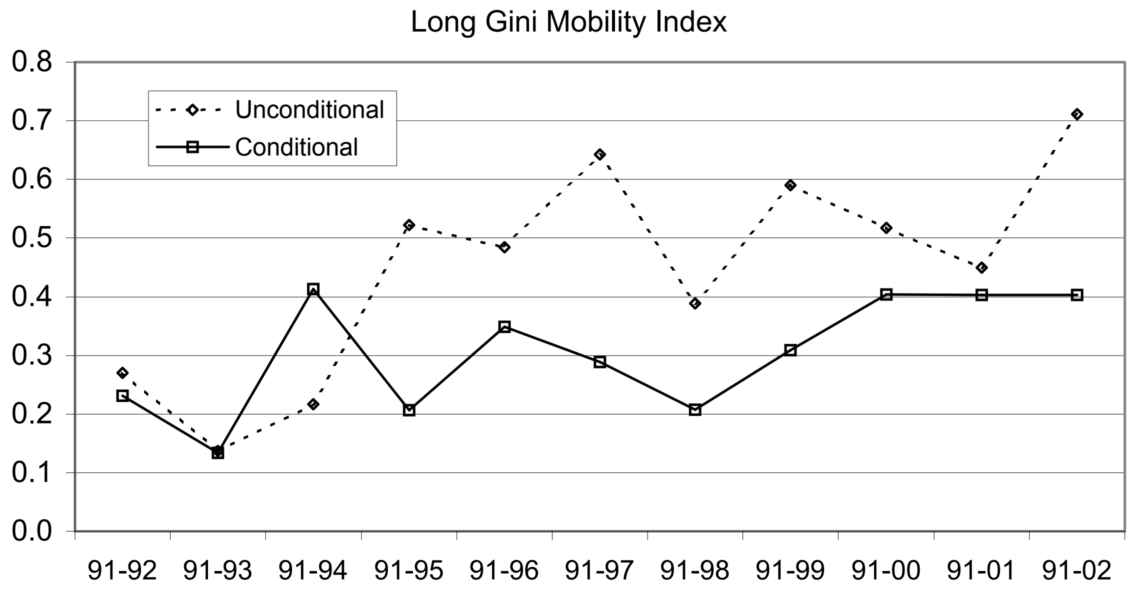
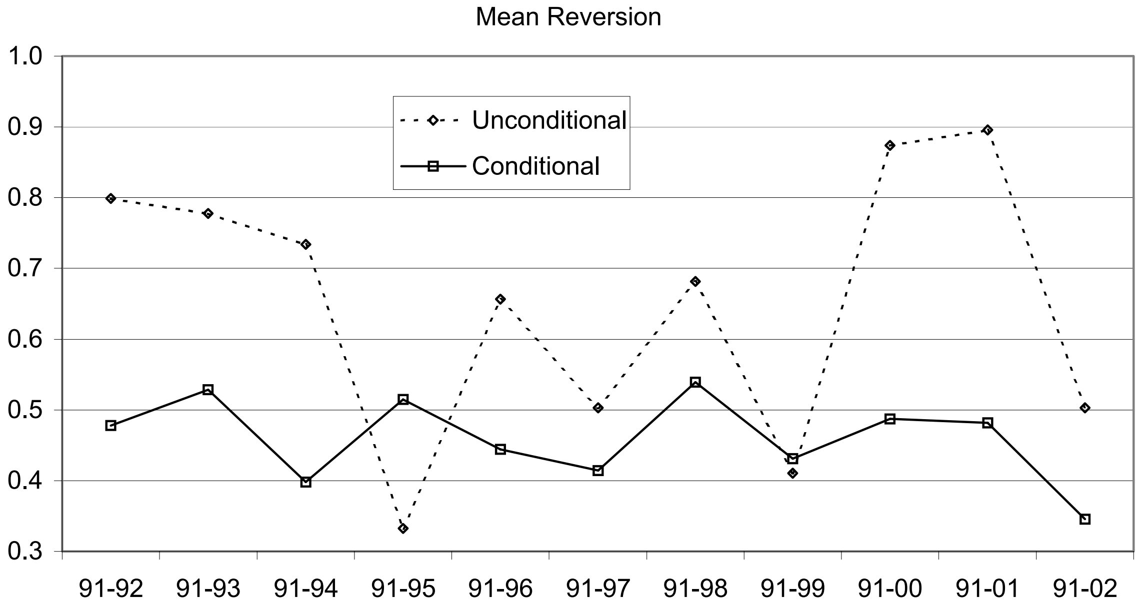


Figure 5: Conditional and Unconditional Cumulative Beta Coefficients



Map 1: Geographic Regions of Israel