HOW INTERNALLY MOBILE IS CAPITAL?

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Regional panel data on capital stocks in Israel are used to test, for the first time, the hypothesis of perfect internal capital mobility. Since the panel data are nonstationary these tests are carried out using panel cointegration methods. The data clearly reject the hypothesis that capital is perfectly mobile in Israel, despite its small size. However, tests suggest that capital might be imperfectly or partially mobile. Attempts to account for the presence of cross-section dependence between panel units overturns the hypothesis of partial capital mobility. At the very least, these results challenge the consensus that perfect internal capital mobility is an innocuous empirical assumption in spatial general equilibrium theory.

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Introduction

A standard assumption in the theory of spatial general equilibrium (SGE) is that there is perfect internal capital mobility (PICM), which ensures that rates of return to capital are equated everywhere within the economy (Roback 1982, Krugman 1991, Glaeser and Gottlieb 2008). In SGE models other factors are assumed to be immobile. In Roback's model the immobility of land plays a central role, whereas in the New Economic Geography (NEG) model unskilled labor is assumed to be immobile. By contrast, PICM is assumed to apply uncritically and ubiquitously. Although internal labor migration might be impeded because people develop attachments to places (Nocco 2009), this argument does not extend to capital.

Empirical investigation of PICM has been impeded by lack of data. There are no data on regional or spatial returns to capital that may be used to test the hypothesis that returns to capital are equated. Nor are there data on regional capital stocks that may be used to test PICM indirectly, by testing restrictions on the relationship between regional capital stocks. It is no doubt for these reasons that we are unable to refer to previous empirical investigations of PICM. We show below that PICM plays an important role in SGE theory. If capital is immobile, or even imperfectly mobile, the comparative statics of SGE are mitigated compared to their counterparts under PICM.

In this paper we use capital stock data for Israel, constructed using the methodological proposal in Beenstock, Ben Zeev and Felsenstein (2011), to carry out indirect tests of PICM. Specifically, annual capital stock data are generated for nine regions of Israel during 1987 – 2010. These data are used to test PICM according to the theory described in the next section. Unfortunately, direct tests of PICM are not feasible since data on spatial returns to capital do not exist.

Theory

Two theoretical issues are considered. First, if capital is perfectly mobile internally, restrictions apply to the relationship between capital-labor ratios (k = K/L) between regions. If these restrictions do not apply empirically, we may reject PICM. On the other hand, capital may be imperfectly mobile, or even completely immobile. Secondly, we show that if PICM does not apply, comparative static shocks on SGE are qualitatively the same, but quantitatively smaller.

Implications of PICM for Capital-Labor Ratios

Each region is assumed to produce homogeneous output using a common Cobb-Douglas production technology:

$$Q_j = A_j K_j^{\alpha} L_j^{1-\alpha} \qquad (1)$$

where j labels regions, Q, K and L denote output, capital and labor, and A denotes total factor productivity (TFP). The cost of capital in region j is $r + \delta_j - s_j$ where r is the national rate of interest, δ is the rate of depreciation and s denotes a subsidy to capital investment set by regional policy. It is assumed that all firms can raise finance at the rate r. Firms are assumed to equate the marginal product of capital (MPK) to the cost of capital, hence:

$$MPK_j = r + \delta_j - s_j = \alpha A_j k_j^{\alpha-1} \qquad (2)$$

PICM implies that equation (2) applies across all regions in which case the capital stocks in regions i and j are related:

$$A_j k_j^{\alpha-1} = A_i k_i^{\alpha-1} + d_{ji} \qquad (3)$$
$$d_{ji} = (s_i - s_j + \delta_j - \delta_i)/\alpha$$

If for simplicity $d_{ji} = 0$ equation (3) implies that MPK is equated between regions i and j so that:

$$\ln k_j = \mu \ln k_i + \frac{1}{1-\alpha}\ln\left(\frac{A_j}{A_i}\right) \qquad (4)$$

where $\mu = 1$. PICM predicts that the partial elasticities between pairs of k_j and k_i are unity. If TFP in region j exceeds TFP in region i, the capital-labor ratio in j must exceed its counterpart in region i if PICM applies. More generally, PICM implies:

$$k_j = \left(\frac{A_i k_i^{\alpha-1} + d_{ji}}{A_j}\right)^{1/\alpha-1} \qquad (5)$$

according to which the capital-labor ratio in region j varies inversely with d_{ji} because capital in j is more subsidized than in i, or because it depreciates more slowly. Equation (5) implies that the elasticity of k_j with respect to k_i is:

$$\mu_{ji} = \frac{1}{1+\phi_{ij}} \qquad (6)$$

$$\phi_{ji} = d_{ji} k_i^{1-\alpha} / A_i$$

The elasticity exceeds unity if d_{ji} is negative and it is less than unity if d_{ij} is positive.

In the CES case where:

$$Q_j = A_j [aK^{\rho} + (1-a)L^{\rho}]^{1/\rho} \qquad (7)$$

the marginal product of capital is:

$$MPK_j = aA_j [ak_j^{\rho} + 1 - a]^{\frac{1}{\rho}-1} k_j^{\rho-1} \qquad (8)$$

which, unlike equation (2) is no longer loglinear in k. The counterpart of equation (5) is:

$$k_j = \left[\frac{A_i k_i^{\rho-1} (ak_i^{\rho} + 1 - a)^{\frac{1}{\rho}-1} + d_{ij}}{A_j (ak_j^{\rho} + 1 - a)^{\frac{1}{\rho}-1}} \right]^{1/\rho-1} \qquad (9)$$

If $A_i = A_j$ and d = 0, equation (9) implies that $k_i = k_j$ as expected.

Implications of PICM for Spatial General Equilibrium (SGE)

For simplicity and without loss of generality we assume that labor market participation ratios are 1, that the supply of labor hours is wage inelastic and fixed, so that labor supply is equal to the population. However, because of internal labor mobility regional populations are endogenous. We consider the case of a “small open region”, which is affected by what happens elsewhere, but which is too small to affect other regions.

Profit maximization implies that the demand for labor in region j is:

$$L_j^D = K_j \left(\frac{w_j}{A_j (1-\alpha)} \right)^{-1/\alpha} \qquad (10)$$

i.e. it varies inversely with wages, and directly with TFP and capital. If labor was perfectly mobile wages would be equated between regions. However, we assume that labor may be imperfectly mobile:

$$L_j^S = B_j\left(\frac{w_j}{w^*}\right)^{\theta} \qquad (11)$$

where L^S denotes the supply of labor and B denotes relative amenities in j and w* denotes wages in other regions. If θ = ∞ internal migration is perfect. Because region j is "small", w* is not affected by what happens in region j.

The labor market in region j is assumed to clear. Equating equations (10) and (11) solves for wages in region j:

$$\ln w_j = \frac{\ln K_j + \frac{1}{\alpha}\ln A(1-\alpha) - \ln B_j + \theta \ln w^*}{\theta + \frac{1}{\alpha}} \qquad (12)$$

Wages vary directly with TFP, capital and wages elsewhere, and vary inversely with amenities. Note that if θ = ∞, wages in j equal wages elsewhere (w_j = w*). Otherwise, wages in j vary directly with capital and TFP, and inversely with amenities.

Equilibrium employment is:

$$\ln L_j = \frac{\alpha\theta}{1+\alpha\theta}\ln K_j + \frac{1}{1+\alpha\theta}\ln B_j - \frac{\theta}{1+\alpha\theta}[\ln w^* - \ln A_j(1-\alpha)] \qquad (13)$$

Employment varies directly with capital, amenities and TFP, and varies inversely with wages elsewhere. Note that as labor becomes perfectly mobile (θ → ∞) $\frac{\alpha\theta}{1+\alpha\theta} \to 1$, $\frac{1}{1+\alpha\theta} \to 0$ and $\frac{\theta}{1+\alpha\theta} \to \frac{1}{\alpha}$, so that employment is proportionate to the capital stock and does not depend on amenities.

If labor is paid its marginal product, the marginal product of capital in regions j is equal to:

$$MPK_j = \frac{\alpha}{1-\alpha}\frac{w_j L_j}{K_j} \qquad (14)$$

Equation (14) is obtained by substituting the marginal product of labor into equation (2). It states that MPK is unchanged if the capital stock is proportional to the wage bill. PICM implies that MPK = MPK* if, for simplicity, d = 0 in which case:

$$\ln K_j = \ln \tfrac{\alpha}{1-\alpha} + \ln L_j + \ln w_j - \ln MPK^* \qquad (15)$$

Finally, substituting equations (12) and (13) into equation (15) provides the solution for the capital stock:

$$\ln K_j = \ln B + \frac{1+\theta}{1-\alpha} \ln A(1-\alpha) - \theta \ln w^* + \frac{1+\alpha\theta}{1-\alpha}\left(\ln \tfrac{\alpha}{1-\alpha} - \ln MPK^*\right) \qquad (16)$$

Equations (12), (13) and (16) solve for w, L and K. They imply that the elasticities of wages and employment with respect to the exogenous variables are greater in absolute value under PICM than they are when capital is immobile. For example, the elasticity of employment with respect to TFP is:

$$\frac{d \ln L_j}{d \ln A_j} = \frac{\theta}{1+\alpha\theta} + \frac{\alpha\theta(1+\theta)}{(1+\alpha\theta)(1-\alpha)} \qquad (17)$$

where the first term is the direct effect through equation (13) and assumes that capital is immobile, and the second term is induced by capital mobility. The elasticity of wages with respect to TFP is:

$$\frac{d \ln w_j}{d \ln A_j} = \frac{1}{1+\alpha\theta} + \frac{\alpha(1+\theta)}{(1+\alpha\theta)(1-\alpha)} \qquad (18)$$

where the first term is the elasticity when capital immobile. The counterparts of equations (17) and (18) for amenities are:

$$\frac{d \ln L_j}{d \ln B_j} = \frac{1}{1+\alpha\theta} + \frac{\alpha\theta}{1+\alpha\theta} = 1 \qquad (19)$$

$$\frac{d \ln w_j}{d \ln B_j} = -\frac{\alpha}{1+\alpha\theta} + \frac{\alpha}{1+\alpha\theta} = 0 \qquad (20)$$

The direct elasticity of employment with respect to amenities is positive due to internal labor mobility, but is less than one. Capital mobility increases this elasticity to unity. The direct effect of amenities on wages is negative because it induces internal migration, but capital mobility offsets this effect.

Finally, the elasticities of employment and wages with respect to wages elsewhere (w*) and the marginal product of capital elsewhere (MPK*) are:

$$\frac{d\ln L_j}{d\ln w^*} = -\frac{\theta}{1+\alpha\theta} - \frac{\alpha\theta^2}{1+\alpha\theta} \qquad (21)$$

$$\frac{d\ln L_j}{dMPK^*} = -\frac{\alpha\theta}{1-\alpha} \qquad (22)$$

$$\frac{d\ln w_j}{d\ln w^*} = \frac{\alpha\theta}{1+\alpha\theta} - \frac{\alpha\theta}{1+\alpha\theta} = 0 \qquad (23)$$

$$\frac{d\ln w_j}{d\ln MPK^*} = -\frac{\theta}{1-\alpha} \qquad (24)$$

Notice that an increase in wages elsewhere has no effect on wages in region j because although the direct effect increases wages through out-migration of labor, the outflow of capital has a countervailing effect.

Matters are naturally more complicated if region j is not "small" and if internal migration from region i to j is not symmetrical and varies by i and j. In this case capital mobility has a smaller effect than in equations (19) – (24) because of negative feedback from region j to other regions.

Bringing Theory to Data

Suppose there are regional panel data for k_{jt} and d happens to be zero. Equation (4) may be written as:

$$\ln k_{jt} = \mu_{ji} \ln k_{it} + \frac{1}{1-\alpha_{ji}}\left(\ln A_{jt} - \ln A_{it}\right) + u_{jit} \qquad (25)$$

where u denotes a residual. Suppose that the panel data happen to be nonstationary (as we show below) but they are difference stationary. If TFP share common stochastic trends $\ln A_{jt} - \ln A_{it} \sim I(0)$ whereas $\ln k_j$ and $\ln k_i$ are I(1) time series. Asymptotically therefore, the estimates of μ and α are independent. Even if TFP is unobserved, it is possible to test hypotheses regarding μ which should be unity if capital is perfectly mobile. The test simplifies to:

$$\ln k_{jt} = \psi_{ji} + \mu_{ji} \ln k_{it} + u_{jit} \qquad (26)$$

where ψ_{ji} equals the log difference in average TFP between regions j and i.

We distinguish between strong CIPM where equation (4) holds in every time period, and weak CIPM where it only holds in the long run. In either case the residuals (u) must be stationary so that equation (25) is cointegrated. In the former case, the residuals must be serially independent, whereas in the latter case this restriction need not apply.

If there are N regions there are ½N(N-1) pairwise comparisons of k_j and k_i. The Augmented Dickey-Fuller statistic (ADF) for u_{ij} is used to test for cointegration. The ADF statistic for pairs ji are calculated by carrying out the following regression:

$$\Delta \hat{u}_{jit} = \psi_{ji} + \lambda_{ji} \hat{u}_{jit-1} + \sum_{p=1}^{P} \phi_{jip} \Delta \hat{u}_{jit-p} + \varepsilon_{jit} \qquad (27)$$

$$ADF_{ji} = \frac{\hat{\lambda}_{ji}}{sd(\hat{\lambda}_{ji})} \qquad (28)$$

where P denotes the number of augmentations if the residuals of equation (27) happen to be serially correlated. Cointegration requires that ADF be significantly less than zero. For a single pair the critical value for ADF has been calculated by MacKinnon (1991) and is -3.58 when T = 25 at p = 0.05. There are four possible results:

i) Equation (26) is cointegrated, $\hat{\mu}_{ji} = 1$ and u_{jt} is serially independent, in which case the hypothesis of strong PICM is corroborated between j and i.

ii) If u_{ji} is autocorrelated the hypothesis of weak PICM is corroborated.

iii) Equation (26) is cointegrated but $\hat{\mu}_{ji} \neq 1$. PICM is rejected, but capital is imperfectly mobile. If u_{ji} is not autocorrelated, imperfect capital mobility is strong, otherwise it is weak.

iv) Equation (26) is not cointegrated. PICM is rejected as well as the hypothesis that capital is imperfectly mobile.

Each pair constitutes a separate test of PICM. A joint test of PICM involves examining the ½N(N-1) pairwise comparisons. If $\hat{\mu}_{ji} = 1$ for all pairs then PICM is corroborated universally. If $\hat{\mu}_{ji} \neq 1$ but on average $\bar{\hat{\mu}} = 1$ then PICM is corroborated in general. If capital mobility is imperfect $\bar{\hat{\mu}} \neq 1$. Let GADF denote the group average ADF statistic formed by the ½N(N-1) estimates of equation (28). In panel data the critical value of ADF-bar is normally distributed due to the central limit theorem:

$$z = \frac{\sqrt{\tfrac{1}{2}N(N-1)}\left(GADF - E(GADF)\right)}{sd(GADF)} \qquad (29)$$

This formula is similar to the one first proposed by Im, Pesaran and Shin (2003) for panel unit root tests, and by Pedroni (1999) for panel cointegration tests. The expected value and standard deviation of GADF need to be calculated under the null hypothesis that equation (26) is not cointegrated, because the estimates of λ_{ji} are not significantly less than zero. Notice that if equation (26) is cointegrated, the direction of the regression does not matter asymptotically due to super-consistency (Stock 1987), in which case if equation (26) is reversed, and $\ln k_i$ is regressed on $\ln k_j$, with parameters ψ\` and $\mu$\`, then plimψ = plim(1/ψ\`) and plim $\mu$ = plim(1/$\mu$\`). In finite samples, however, matters may be different.

We use the critical values of E(GADF) and sd(GADF) calculated by Perdoni (1999). These critical values are also likely to be “liberal” because they assume that the residuals are cross-section independent, i.e. $E(u_{ji}u_{j`}u_{i`}) = 0$. This assumption will be incorrect if u_{ji} is correlated with u_{jn} because region j attracts too much capital from all other regions, or because it attracts too little capital. We therefore calculate the residual cross-section correlation matrix, which should be diagonal under the null hypothesis. We use the Breusch – Pagan LM test statistic for cross-section dependence:

$$BP = T\sum_{j=1}^{N-1}\sum_{i=1+j}^{N}\hat{\rho}_{ji.jn}^{2} \approx \chi^{2}_{\frac{1}{2}N(n-1)} \qquad (29)$$

where $\rho_{ji.jn}$ denotes the correlation between u_{ji} and u_{jn} and BP is expected to be zero under the null hypothesis of no cross-section dependence.

If the null hypothesis is rejected, there are two main possibilities; the cross-section dependence may be weak or strong (Chudik, Pesaran and Tosseti 2013). In the former case the cross-section dependence is spatial and localized (Anselin 1988) whereas in the latter case the dependence is generic and is induced by common factors, which may be observed or unobserved. In the former case shocks to u_{ji} dissipate across space, whereas in the latter case they do not. The two cases have an epidemiological interpretation. Weak cross-section dependence is "contagious" in the sense that u_{ji} has a causal effect on u_{jn} where region n is a first-order neighbor of region j. However, the epidemic "dies out" because u_{ji} has no domino effect on regions that are remote from j. By contrast, strong cross-section dependence is induced by regional heterogeneity in the effect of one or more common factor on u_{ji}. The epidemic does not spread because of contagion but because all regions are susceptible to various degrees to the same common cause.

Pesaran (2013) suggested the following test for weak cross-section dependence:

$$CD = \sqrt{\frac{TN(N-1)}{2}}\bar{\hat{\rho}} \approx N(0,1) \qquad (30)$$

If the average value of ρ is not significantly different from zero the null hypothesis of weak cross-section dependence cannot be rejected. Unlike BP, CD depends on the sign of ρ. For example, if N = 3, T = 100 and the three values of ρ_{ji} are 0.4, 0.4 and -0.8, CD = 0 but BP = 96, in which the cross-section dependence is weak (spatial). If instead the values of ρ_{ji} are 0.4, 0.4 and 0.8, BP still equal 96 but CD = 32, in which case the cross-section dependence is strong. In general, both types of cross-section dependence may be present.

The spatial variant of equation (26) is:

$$\ln k_{jt} = \psi_{ji} + \mu_{ji} \ln k_{it} + \delta_{ji} \ln \tilde{k}_{jt} + \pi_{ji} \ln \tilde{k}_{it} + u_{jit} \qquad (30)$$
$$\tilde{k}_{jt} = \sum_{n \neq j}^{N} w_{jn} k_{nt} \qquad \tilde{k}_{it} = \sum_{n \neq i}^{N} w_{in} k_{nt}$$

where w denote spatial weights row-summed to one, $\tilde{k}_j$ denotes the spatial lagged dependent variable, and $\tilde{k}_i$ denotes its spatial Durbin counterpart. If the data are stationary the spatial lag coefficients (δ and π) need to be estimated by maximum likelihood (Anselin 1988). However, if the data happen to be nonstationary, OLS estimates of these parameters are super-consistent (Beenstock and Felsenstein 2015). Equation (30) is a double spatial lag model because it specifies spatial lags in the vicinities of regions j and i. The elasticity of k in region j with respect to k in region i is:

$$\mu_{ji} + \delta_{ji} \frac{\partial \ln \tilde{k}_j}{\partial \ln k_i} + \pi_{ji} \frac{\partial \ln \tilde{k}_i}{\partial \ln k_i} \qquad (31)$$

It depends on the direct elasticity μ as well as the two spatial elasticities.

For strong cross-section dependence Pesaran (2007) has suggested the common correlated effects (CCE) estimator in which equation (26) is specified as:

$$\ln k_{jt} = \psi_{ji} + \mu_{ji} \ln k_{it} + \kappa_{ji} \ln \bar{k}_t + u_{jit} \qquad (32)$$

where $\bar{k}$ denotes the average capital-labor ratio and κ_{ji} denotes the loading of this common factor on the relation between k_j and k_i. Critical values for panel cointegration tests using CCE have been calculated by Banerjee and Carrion-I-Silvestre (2011).

A final variant of equation (26) takes account of regional investment grants. Let Z_{jt} denote the cumulative stock of investment grants in region j at the beginning of period (year) t. Theory predicts that capital labor ratios vary directly with Z. Conditional on k_i, k_j should vary directly with the difference between Z_j and Z_i:

$$\ln k_{jt} = \psi_{ji} + \mu_{ji} \ln k_{it} + \eta_{ji} (Z_{jt} - Z_{it}) + u_{jit} \qquad (33)$$

At first equation (26) is freely estimated, which delivers μ-bar, which is the average of the estimates of μ_{ji}. PICM predicts that μ-bar is one. It may exceed one for some pairs and be less than one for others, unless PICM is strictly applied to all pairs. More generally, μ-bar summarizes the degree of internal capital mobility, and is a number that varies between zero (capital immobility) and one (PICM). If, for example, μ-bar is 0.6 it means that internal capital is 60 percent mobile. To test whether μ-bar is significantly less than unity, we impose the restriction that $\mu_{ji} = 1$ for all pairs, calculate the ADF statistics for the new pairwise residuals, and determine whether the restricted model is cointegrated. If it ceases to be cointegrated, we may reject PICM as the null hypothesis.

If PICM happens to be rejected in favor of imperfect capital mobility, we test the secondary hypothesis that capital mobility varies inversely with the distance between pairwise nodes. Since equation (26) is a pairwise regression estimated using time series observations between j and i, this secondary hypothesis is investigated indirectly by testing whether the estimates of μ_{ji} vary inversely with the distances between j and i.

3. Data

Annual capital stock data for 9 regions of Israel (see map) were calculated during 1987 – 2010 using the method proposed by Beenstock, Ben Zeev and Felsenstein (2011). The capital stock comprises plant and machinery. This method calculates plant directly from regional data on building completions (square meters) in the business sector published by the Central Bureau of Statistics (CBS). It allocates machinery at the national level to the 9 regions according to the ratio of machinery to plant across the economy. For example, if the value of plant in a region is \$100, and the ratio of machinery to plant across the economy is 1.3, the value of machinery in the region is imputed to be \$130 so that K = \$230. Data on employment for these 9 regions were constructed by us from Labor Force Surveys (CBS), and data for earnings (deflated by the national CPI) were constructed by us from Household Income Surveys (CBS). Since geographic disaggregation in these surveys is not continuously available prior to 1987, this determines the starting point for our investigation.

Capital-labor ratios (k) are plotted in Figure 1 in 1000s of shekels at 2005 prices. The Haifa region stands out as the most capital-intensive region of Israel because heavy industry has been concentrated in Haifa since Ottoman times. There are persistent and substantial differences between capital-labor ratios in the rest of the country. In 1987 the Dan region was the least capital intensive, but by 1996 it exchanged positions at the bottom of the distribution with Krayot. The Tel Aviv region, which in 1987 was in 4th position, temporarily moved up to 2nd position in 2003. On the whole, however, positions in the distribution appear to be quite stable. Following the wave of mass migration from the former USSR (1989 – 1995) capital-labor ratios naturally decreased especially in Haifa, which absorbed many immigrants. Subsequently, capital labor ratios recovered, eventually surpassing what they were in the late 1980s.

Since 1967 the Ministry of Trade (now the Ministry of Economics) has operated an Investment Center, which provides investment grants as part of its regional development policy. Businesses in designated regional development zones (A, B and C) are eligible to apply to the Investment

Center for investment grants, which are awarded as percentages of the total investment. These percentages are highest in zone A and lowest in zone C. Priority is given to export businesses, and to industry rather than to services. The criteria have varied over time as have the zones eligible for regional development support. Figure 2 plots the allocation of investment grants at constant 2005 prices by the Investment Center in each of the 9 regions. The main beneficiaries have been the North and South, and since 2007 the budget of the Investment Center has been cut-back considerably. By contrast the central regions (excluding Jerusalem) have received almost nothing.

Figure 3 plots the cumulative (since 1967) development grants received by the 9 regions. Since these are stocks, the data can only increase over time. However, these stocks no longer increase in regions that have ceased to be eligible for investment support. By contrast, the stock has increased in North and South and to some extent in Jerusalem.

Table 1 Panel Unit Root Tests

	IPS		CIPS	
d	0	1	0	1
lnk	1.07	-3.92	-1.51	-3.75
lnZ	-8.89	-8.15	-2.28	-3.64

Notes: Order of differencing denoted by d. IPS: Unit root test due to Im, Pesaran and Shin (2003). CIPS: Unit root test due to Pesaran (2007)

Panel unit roots tests are reported in Table 1 for the data in Figures 1 and 3. The IPS statistics assumes that there is no cross-section dependence between the panel units, whereas the CIPS statistics assume that there is strong cross section dependence. The IPS statistic confirms that lnk is difference stationary, as does the CIPS statistic. Matters are more complicated in the case of the data in Figure 3 where both IPS and CIPS suggest that lnZ may be stationary. The problem is that for most regions lnZ maybe stationary, but in North, South and Jerusalem it is clearly nonstationary. In what follows it is assumed that lnZ is difference stationary.

Results

Model 1 in Table 2 tests CIPM by estimating equation (26) with μ_{ji} imposed to be one. The GADF statistic (-0.691) greatly exceeds its critical value (-2.22), which clearly rejects CIPM.

There is extensive cross-section dependence between the 36 sets of residuals (BP = 303.7) since the critical value of chi square with 36 degrees of freedom is approximately 50. The average correlation between the 36 sets of residuals is 0.062, which is statistically significant since CD > 1.96. Therefore, the null hypothesis of weak cross-section dependence is clearly rejected. On this basis the null hypothesis of CIPM, both strong and weak, is also clearly rejected.

Model 2 in Table 2 does not impose the restriction that $\mu_{ji} = 1$. When this restriction is lifted the average estimate of μ is 0.701, and the GADF statistic decreases sharply (-2.307), which nevertheless is slightly larger than its new stricter critical value (-2.489). Therefore, model 2 comes close to being panel cointegrated. Cross-section dependence is even stronger than in model 1. The large standard deviation of μ (0.526) implies that the estimates of μ are widely dispersed; in 9 cases μ exceeds unity but μ is always positive. Model 2 indicates that there is substantial heterogeneity in μ, which is inconsistent with absolute CIPM, but may be consistent with relative CIPM. When homogeneity is imposed by restricting $\mu_{ji} = 0.7$, GADF increases sharply from -2.307 to -1.407, which clearly rejects homogeneity.

Table 2 Tests of CIPM

Model	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
$\bar{\hat{\mu}}$	1	0.701 (0.526)	1	0.700 (0.499)	1	0.0304 (0.402)	1	-0.077 (0.627)
$\bar{\hat{\delta}}$					-0.288 (2.560)	0.216 (1.839)		
$\bar{\hat{\pi}}$					0.043 (2.672)	0.604 (1.794)		
$\bar{\hat{\eta}}$			0.019 (0.349)	0.035 (0.161)				
$\bar{\hat{\kappa}}$							0.292 (0.790)	0.950 (0.794)
$GADF_1$	-0.691	-2.307	-1.365	-2.486	-2.683	-2.967	-2.440	-2.843
GADF*	-2.220	-2.489	-2.489	-2.860	-2.860	-3.191	-3.	-3.55
BP	303.7	135	257.4	97.5	113	93.04	189.3	121.3
CD	7.663	8.736	8.22	8.870	4.700	0.006	3.63	2.48
$\bar{\hat{\rho}}$	0.062	0.071	0.067	0.072	0.038	0.00005	0.030	0.002

Notes: Standard deviations in parentheses. $GADF_1$ 1st order group ADF statistic of residuals. BP Breusch-Pagan LM test statistic for cross-section dependence in pairwise residuals. CD test statistic for weak cross-section dependence. $\bar{\hat{\rho}}$ Average cross-section correlation. In models 1, 3, 5 and 7 μ is imposed at unity. GADF* Critical value of GADF at p = 0.05 one tail: Models 1 -6, Pedroni (1999) table 2, models 7-8, Banerjee and Carrion-I-Silvestre (2011) table 1.

Figure 4 plots the relationship between the estimates of μ_{ji} from model 2 and the distance between j and i. If capital mobility varied inversely with distance, this relation should be negative. However, there is no relation between the two.

Model 3 in Table 2 refers to equation (33) with μ imposed at unity. The specification of regional investment grants causes GADF to decrease substantially from -0.691 in model 1 to -1.365, which indicates that investment grants may have a role in the determination of regional capital-labor ratios. However, GADF falls well short of its critical value. When μ is estimated unconstrained, as in model 4, it is similar to its estimate in model 2, GADF becomes more negative than in model 2, but falls short of its critical value, and the p-value of model 4 is larger than that of model 2. The mean estimates of η in models 3 and 4 are positive, as expected, but they are widely dispersed (standard deviation of 0.349), and 12 of the 36 estimates are negative in model 3.

Models 1 – 4 are strongly cross-section dependent. Models 5 and 6 add spatial dynamics to models 1 and 2 (as in equation 30), which is intended to pick-up weak (spatial) cross-section dependence. Indeed, the BP statistic decreases sharply from 303.7 to 97.5 in the case of model 1, and less dramatically in the case of model 2. Also, the CD statistic decreases and even ceases to be significant in model 6. In model 5 there is negative spatial dependence in the vicinity of region j and positive spatial dependence in the vicinity of region i, meaning that if k increases in the neighborhood of region j, k in region j is adversely affected, but the opposite happens if k increases in the vicinity of region i. These spatial effects transform the GADF statistic from -0.69 in model 1 to -2.64 in model 5. However, when CIPM is not imposed (as in model 6) GADF becomes more negative, the average estimate of μ is close to zero, and 14 out of 36 estimates of μ are negative. In both models GADF falls short of its critical value, so neither model is panel cointegrated at conventional levels of probability.

Finally, results for the common correlated effects estimator (equation 32) are reported in models 7 and 8. CCE is expected to reduce strong cross-section dependence, which it does. CD in model 7 is 3.63 compared to 7.663 in model 1, and it is 2.48 in model 8 compared to 8.73 in model 2.

However, CD in models 7 and 8 continues to be statistically significant, suggesting that further common factors may be required to take account of strong cross-section dependence. On average the loadings on the common factor are positive, so that the average elasticity of k with respect to average k is 0.29 in model 7 and 0.95 in model 8. However, there are 22 negative loading in model 7 and only 2 in model 8. The sharp decrease in GADF especially in model 7 compared to model 1 indicates the statistical importance of the common factor. However, GADF continues to fall short of its critical values. Moreover, in model 8 μ is almost zero.

Inspection of the residual correlation matrix indicates that cross-section dependence is generic. Not only are pairwise residuals correlated for given origins and destinations, they are correlated when origins and destinations are separate. Therefore, the cross-section correlation is not induced by origin – destination fixed effects. The residuals between j and i and j and i\` may be correlated because they share j in common. However, the residuals between j and i are just as likely to be correlated as the residuals between j\` and i\`.

Strong cross-section dependence is present in all the results reported in Table 2. Intuitively, one learns less from dependent experiments than from independent experiments. The critical values for GADF are therefore too liberal because they assume that our 36 "experiments" are independent. Suppose, for example, that in model 2 GADF had been -3 instead of -2.307. In the absence of cross-section dependence model 2 would have been panel cointegrated. Matters might be different, however, if the cross-section dependence is sufficiently strong. There would be a dilemma because critical values for GADF in the presence of cross-section dependence are not available. Baltagi, Bressone and Pirotte (2007) and Beenstock and Felsenstein (2015) have shown that ADF tests are reliable in spatially dependent panel data, provided the dependence is not too great. The implications of strong cross-section dependence for the critical values of GADF have yet to be explored. Since in Table 2 GADF is always greater than its critical value, this dilemma does not arise.

It was mentioned that if the data are nonstationary and cointegrated, there is no meaning, asymptotically, to the direction of regression models such as equation (26). Reversing the direction of the regression by regressing $\ln k_i$ on $\ln k_j$ should produce the same result. In finite samples with T = 24, however, matters might be different. To investigate this, model 2 in Table 2 was reversed. The mean estimate of $1/\mu$ is 1.114 instead of 1.42, GADF is -2.19 instead of -

2.307, BP is 130 instead of 135 and CD is 16.15 instead of 8.736. Therefore, reversing the regression makes a difference, but it is not sufficiently great to alter the results. In fact, GADF was slightly larger in all the models (model 4 -2.344, model 6 -2.876, model 8 -2.592). Therefore, the results in Table 2 are robust with respect to potential finite sample bias.

Conclusions

In the absence of data on regional returns to capital, estimates of regional capital stock data for Israel are used to carry out indirect tests of the hypothesis of perfect internal capital mobility. This issue is important because spatial general equilibrium theory assumes that capital is perfectly mobile within countries. Indeed, this is the first time that tests of internal capital mobility have been undertaken.

Since the panel data in the study are nonstationary, the hypothesis of perfect internal capital mobility is carried out using panel cointegration methods. However, matters are complicated by the presence of cross-section dependence within and between the panel units, which weakens standard panel cointegration tests. These tests distinguish between perfect capital mobility, imperfect or partial capital mobility, and no capital mobility. Using annual data for 9 regions of Israel during 1987 – 2010, the hypothesis of perfect capital mobility is clearly rejected. Matters are less clear-cut regarding imperfect capital mobility. At conventional levels of probability, the data reject the hypothesis of partial capital mobility too. However, at laxer levels of probability the data do not reject this hypothesis.

Attempts to account for strong and spatial (weak) cross-section dependence were only partially successful. The hypothesis of partial internal capital mobility is rejected in these specifications. If in a small country such as Israel it is difficult to find evidence in favor of perfect or even imperfect capital mobility, in large countries such as the US and the UK it might be even more difficult. At the very least, these results challenge the consensus that perfect internal capital mobility is an innocuous empirical assumption in spatial general equilibrium theory.

References

Anselin J-L. (1988) *Spatial Econometrics: Methods and Models*, Kluwer, Boston.

Banerjee A., Carrion-I-Silvestre J.L. (2011) Testing for panel cointegration using common correlated effects estimators. Dept of Economics, University of Birmingham.

Baltagi B.H., Bressone G., Pirotte A. (2007) Panel unit root tests and spatial dependence. *Journal of Applied Econometrics*, 22: 339-360.

Beenstock M., Ben Zeev N, Felsenstein D. (2011) Capital deepening and regional inequality: an empirical analysis. *Annals of Regional Science*, 47: 599-617.

Beenstock M, Felsenstein D. (2015) Spatial spillover in housing construction. *Journal of Housing Economics*

Chudik A., Pesaran M.H., Tosetti E. (2011) Weak and strong cross-section dependence and estimation of large panels. *Econometrics Journal*, 14: C45-C90.

Glaeser E.L. Gottlieb J.D. (2009) The wealth of cities: agglomeration economies and spatial equilibrium in the United States. *Journal of Economic Literature*, 47: 983-1028.

Im K.S., Pesaran M.H. and Shin Y. (2003) Testing for unit roots in heterogeneous panels. *Journal of Econometrics*, 115: 53-74.

Krugman P. (1991) *Geography and Trade*. MIT Press.

Nocco A. (2009) Preference, heterogeneity and economic geography. *Journal of Regional Science*, 49: 33-56.

Pedroni P. (1999) Critical values for cointegration tests in heterogeneous panels with multiple regressors. *Oxford Bulletin of Economics and Statistics*, 61: 653-670.

Pesaran M.H. (2007) A simple panel unit root test in the presence of cross section dependence. *Journal of Applied Econometrics*, 22: 265-312.

Pesaran M.H. (2006) Estimation and inference in large heterogeneous panels with a multi-factor error structure. *Econometrica*, 74: 967-1012.

Pesaran MH. (2013) Testing weak cross-sectional dependence in large panels. *Econometric Reviews*

Roback J. (1982) Wages, rents and the quality of life. *Journal of Political Economy*, 90: 1257-1278.

Stock J. H. (1987) Asymptotic properties of least squares estimators of cointegrating vectors. *Econometrica*, 55, 1035-1056.

Figure 1 Capital – Labor Ratios

Thousands of shekels at 2005 prices

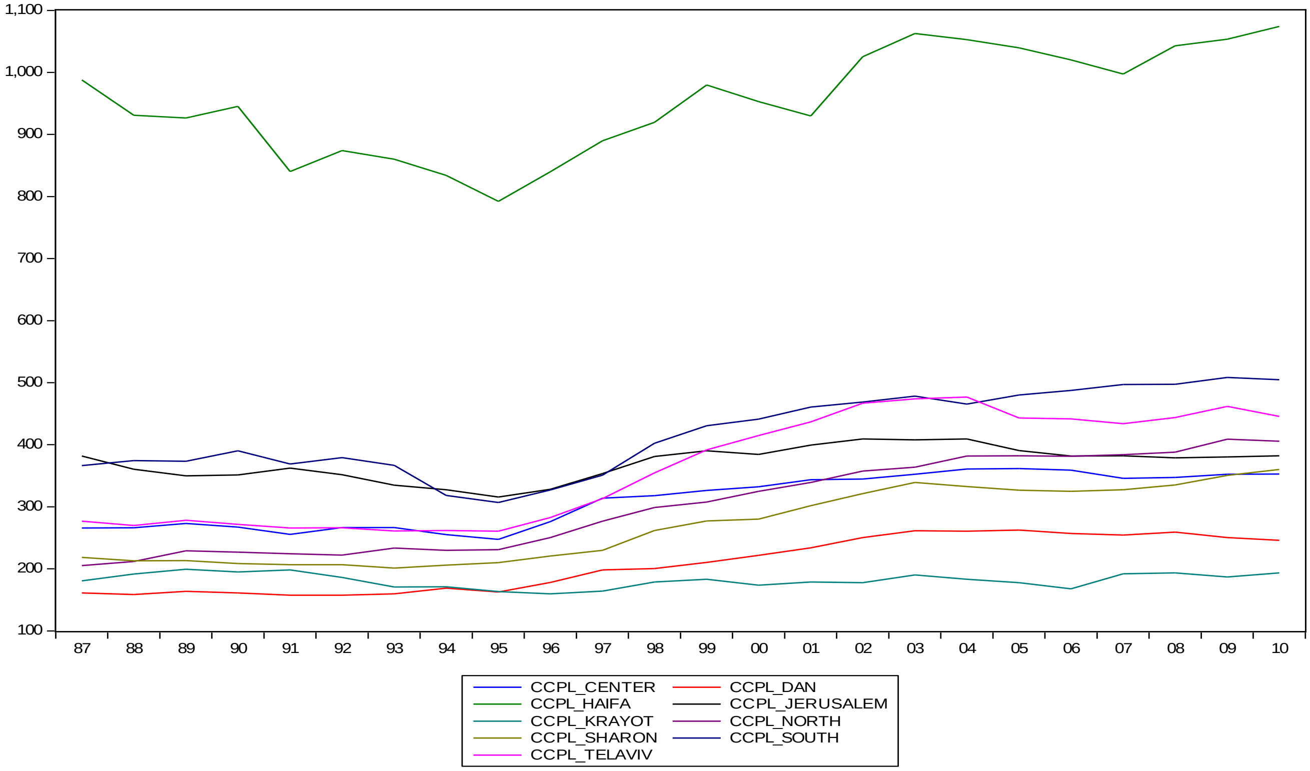


Figure 2 Investment Grants (shekels at 2005 prices)

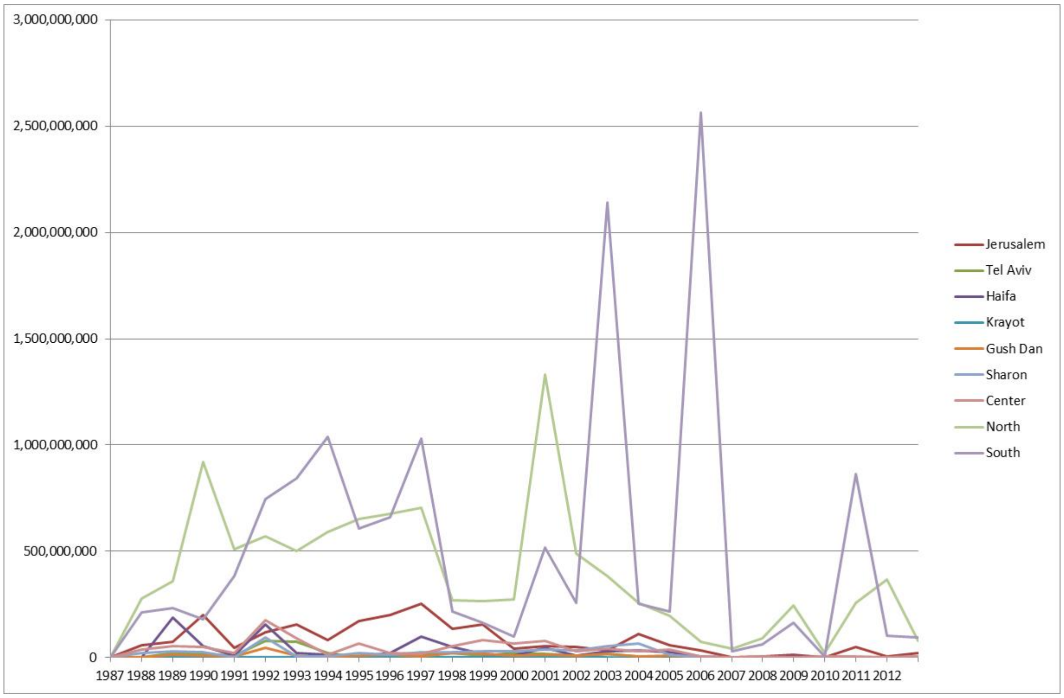


Fig 3 Cumulative Capital Investment by the Investment Center (shekels at 2005 prices)

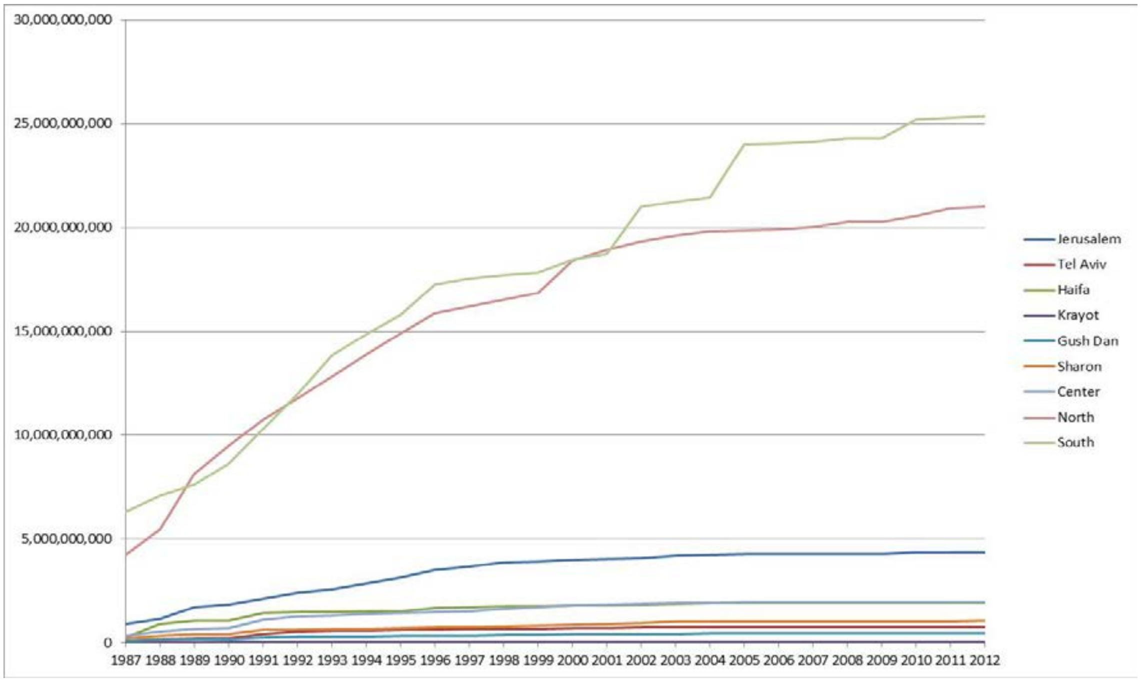
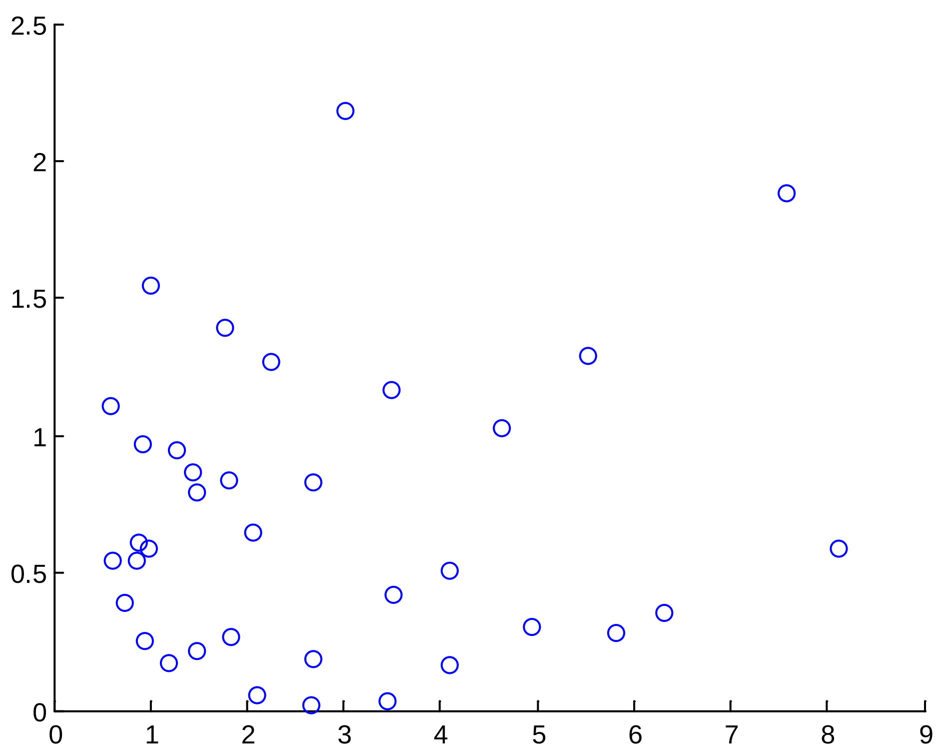
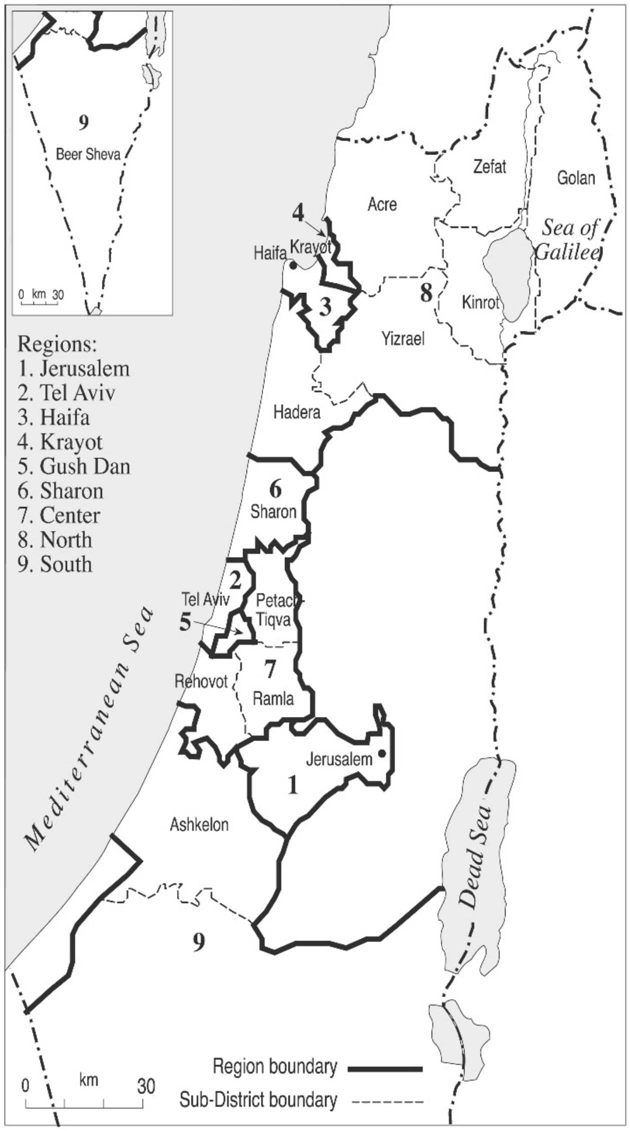


Figure 4 Relation between μ and Distance




9
Beer Sheva
0 km 30
Regions:
1. Jerusalem
2. Tel Aviv
3. Haifa
4. Krayot
5. Gush Dan
6. Sharon
7. Center
8. North
9. South
Zefat
Golan
Acre
Sea of Galilee
Haifa
Krayot
Kinrot
Yizrael
Hadera
Sharon
Tel Aviv
Petach Tiqva
Mediterranean Sea
Rehovot
Ramla
Jerusalem
Ashkelon
Dead Sea
Region boundary
Sub-District boundary
0 km 30

Map