A Panel Data Investigation of the Relationship Between Urbanization and Growth

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Abstract

Urban economists have long sought to explain the relationship between urbanization levels and output. In this paper we revisit this question and look for a relationship between urbanization and growth using non-stationary panel data techniques. Our results show that a long run relationship between urbanization, output per worker and capital per worker cannot be rejected for either our sample of 30 developing countries or our sample of 22 developed countries. In addition, we estimate the long run average effects on GPDW of urbanization and capital. These results offer new insights and potential for dynamic urban models rather than the simple cross-section approach.

1 Introduction

Urban economists have long been attempting to answer the question of why cities exist. In particular, recent research has focused on the idea that cities capture some sort of agglomeration economies-production in urban areas benefits from some increasing returns to scale which are not present in rural environments. Urban economists have gone further to separate these agglomerations into two categories: localization economies, economies of scale present because of industrial clustering in cities and urbanization economies, economies of scale present because of the overall size of city. Localization economies are external to the firm but internal to the industry. Most of the articles presented with regards to output and urbanization have focused on urbanization economies and not localization economies.

Given that urban structure is hypothesized to influence output levels another related question is how urbanization affects economic development: what is the role of urbanization levels in developing and developed countries. A long running debate in development economics has been whether developing countries

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have become overurbanized. In Moomaw and Shatter (1993) the debate is characterized as that between the traditionalists as represented by Todaro's works, for example his piece (1995) which claims that less developed countries are overurbanized, and the modernists as represented in the work of Wheaton and Shishido (1982), which claim that large cities are necessary to realize economies of scale. Unfortunately, there are not many empirical studies which look at this question. Further, the empirical research in the literature is either based on cross-section studies or very limited panels which are unable to truly capture the dynamic nature of the question.

Mera (1973) presents the discussion as to whether urban areas in developing countries are "too large." The argument is based on diseconomies which can be present in cities which are too large and no longer efficient. Two reasons to suspect that large cities are no longer efficient are discussed: (1) social overhead costs in large cities could be large enough to outweigh gains in production and (2) even though urban residents tend to have higher per capita incomes, per capita incomes measure average productivity and not marginal productivity. In fact it could be that marginal productivity in urban areas is less than that in rural areas. Mera's results do not support the hypothesis that cities are "too large." He states that policies taken to develop less urbanized areas in developing countries should not be taken on efficiency grounds as urban residents tend to earn higher incomes; but such development policies may make sense if the goal is to equalize incomes across regions.

An early paper by Wheaton and Shishido (1982) also addresses the idea of urban agglomerations. Again Wheaton and Shishido point to a debate among development economists on whether developing countries have become too urbanized. In particular, there is concern about so-called "primal cities." The "primal cities" are represented by usually one or two major cities in developing countries whose populations dominate the overall urban population of the country. In particular, these primal cities are usually not accompanied by a system of mid-size cities. The development of primal cities can be seen as a positive as city growth is necessary to capture agglomerations in production. However, many feel that the social costs of these cities outweigh any production advantages. In their paper, Wheaton and Shishido seek to test this question.

They hypothesize that the relationship between economic growth and urbanization is non-linear and can best be approximated by an exponential growth function. Further they include the amount of arable land for a country and political decentralization as explanatory variables. Their results show that this function fits the data better than a linear representation. The interpretation of the non-linearity is that urban agglomerations refer to the intensity of capital usage such that at a certain stage of development capital saturation occurs and beyond a critical point, urbanization moves from a phase of centralization to decentralization.

Brueckner (1990) presents another model for third world urbanization. In his paper, Brueckner looks very carefully at the two reasons for urbanization in developing countries: rural to urban migration and population growth. In particular he concentrates on rural to urban migration. He sets up a monocentric model which seeks only to answer the question as to whether or not urbanization is driven by the hypothesis that rural and urban residents will move to equalize incomes. He also sets up an empirical model which allows slower adjustment toward equilibrium, a standard stock adjustment model. His results show that the ratio of rural to urban incomes is important in determining urbanization levels and that land rents do not seem important in determining urbanization levels.

Two purely empirical studies were done by Moomaw and Shatter (1993, 1996). In the first article Moomaw and Shatter test their hypothesis that urbanization levels should influence growth by separating the urbanization variable into three separate variables: population in the largest city in the country, metropolitan concentration and percent of the population living in urban areas. The dependent variable in their study is the growth rate of GNP. Their goal is to separate the effects of agglomeration economies and the possibility that a "primal city" may be too large. Their results show that metropolitan concentration has a positive relationship to growth while the population of the largest city has a negative impact. They interpret these results as that metropolitan concentration may be responding to market forces while development in a primal city may be cause by non-market forces, such as government intervention.

In their second article, Moomaw and Shatter (1996) again test the effects of urban percentage, metropolitan concentration and primacy. They find that with respect to urban percentage, countries with smaller labor shares in agriculture and higher shares in industry tend to be more urbanized; countries with higher literacy rates also tend to be more urbanized; urbanization increases with per capita GDP and exports as a percentage of GDP. With regard to metropolitan concentration they find that there is a negative relationship between metropolitan concentration and export share of GDP; metropolitan concentration decreases with share of agriculture and increases with share of industry. Finally with regards to primacy they find that political forces are important.

The articles presented above all depend on large cross-section dimensions of data and limited, if more than one, time series observations. Where panel techniques are used they are rudimentary and do not fully exploit the importance of the time dimension. The model presented here, unlike the above, follows more from the growth literature than the literature of urban economics in developing countries per se. In this paper we investigate the difference between the relationship of urbanization and growth over time through panel data and in the simple cross section.

The main idea of the dynamic model we use comes from the neoclassical growth literature which sets out a dynamic optimization problem for the economic individual constrained by some production function. An example of this theory is given by Lucas (1988) and his attempts to explain economic growth in developed and developing countries. His paper is not among those concerned with the convergence theories of growth such as the article by Barro (1991). Rather it solves models with utility maximization given production constraints where human capital, learning by doing and comparative advantage in trade drive growth. He also alludes to, though never solves, an example where cities could cause growth by capturing certain agglomerations in production. This is the background philosophy for the model presented below. Although the model presented here does not solve the consumer maximization problem, it does set out a production function which, if properly specified could enter a growth model as a pertinent constraint.

Section 2 of this Chapter presents the Cobb-Douglas production function model used in the paper. In this model urbanization is added as a shift factor. Section 3 presents the empirical results of the paper distinguishing between the dynamic results on the model including non-stationary variables, and the results from cross section regressions. Section 4 offers concluding notes.

2 The Model

The model proposed here uses a Cobb-Douglas production function which restricts the sum of exponents on capital and labor to one. The production function is defined for each country and each year:

$$Y_{it} = A_{it}(U_{it})^{\lambda_i}(K_{it}^{\beta_i} N_{it}^{1-\beta_i}) \tag{1}$$

where Y_{it} is GDP for country i in time period t, U_{it} is the percent of the population living in an urban area, K_{it} is capital stock, and N_{it} is the number of workers. A_{it} is the specification for technology and is the element which introduces a stochastic element into the model. Technology and urbanization levels in this model both act as shift factors.

$$A_{it} = e^{\alpha_i + \varepsilon_{it}} \tag{2}$$

Normalizing by N and taking the natural log forms the following model:

$$\ln Y_{it}^* = \alpha_i + \beta_i \ln K_{it}^* + \lambda_i \ln U_{it} + \varepsilon_{it} \tag{3}$$

where $Y_{it}^* = \frac{Y_{it}}{N_{it}}$ and $K_{it}^* = \frac{K_{it}}{N_{it}}$.

The panel model here allows each of the cross-sections to have a unique intercept. In this model, α_i can be interpreted as a shift factor in production caused by technological change. Thus, there is a stochastic element to technology which varies about a mean. Technology growth has a constant trend, α_i and a random shock that acts on the trend, ε_{it}. β_i can be interpreted as the elasticity of capital per worker with respect to production output per worker and λ_i the urbanization elasticity. Allowing varying slopes as well as intercepts allows the individual countries to have heterogeneous production functions and means that the regression coefficients from each cross-section are estimated independently.

The data used in this paper comes from the Penn World Tables and the World Bank "Social Indicators of Development." The Penn World tables provide yearly observations on non-residential capital stock per worker, KAPW, and real GDP per worker, RGDPW. Both are reported in 1985 international prices. The World Bank "Social Indicators of Development" provides data on percent of the population living in an urban area. The data are recorded in yearly observations from 1965-1989. There are two potential groups of the data: developed countries and developing countries. The set of developing countries, Group 1, has 30 country observations and includes countries from Africa, Central America, South America and Asia. The set of developed countries, Group 2, has 22 observations comprised of European, Asian, North American countries and Australia and New Zealand. As outlined in the model, all variables are in log form. All estimation and testing is done in GAUSS 3.0 using the package COINT 2.0.

With 25 years of observations for each cross-section series, we introduce a substantial time dimension which allows us to exploit current results in the time series and dynamic panel literature which allow us to test for unit roots and cointegration. The potential presence of unit roots and cointegrating relationships in the data opens up to us a whole new wealth of theory and interpretation unavailable in the cross section.

3 Empirical Results

3.1 Dynamic Panel Data Results

3.1.1 Testing for Non-Stationarity and Cointegration in Panel Data

In this section we summarize the non-stationary panel data tests for unit roots and cointegration we will be using and offer some intuition behind the testing. The test of the null hypothesis of cointegration states that under the H_0 there exists a long run relationship between the natural logs of output per worker, capital stock per worker, and urbanization levels. The model allows for varying intercepts and varying slopes and thus a cointegration test for heterogeneous cross-sections is applicable. An intuitive interpretation of the null hypothesis would be that if there exists a long run relationship between these three variables then including urbanization levels in the production function specification is reasonable and helpful in describing growth in output in the long run.

The first step to determining a potentially cointegrated relationship is to test whether the variables involved are stationary or non-stationary, i.e., whether the individual series contain unit roots. [1]If all the variables are stationary, then traditional estimation methods can be used to estimate the relationship between the variables, in this case urbanization, KAPW and GDPW. If, however, at least one of the series is determined to be non-stationary then more care is required.

The test we use to test for stationarity was first presented by Im, Pesaran and Shin (1995). In their paper, Im, Pesaran and Shin (IPS) present a statistic testing the H_0 of non-stationarity for a variable observed in a panel. The statistic is based on the augmented Dickey Fuller (ADF) test widely used in the time series literature. Recall that the ADF test in the time series case can be written:

$$\Delta y_t = \alpha + \beta y_{t-1} + \Sigma_{j=1}^{p_i} \gamma_j \Delta y_{t-j} + v_t. \tag{4}$$

The null hypothesis of non-stationarity is written: $H_0 : \beta = 0$ versus the $H_a : \beta < 0$. An equivalent way to express the null and alternative hypothesis is to use the notation: H_0 : y is an $I(1)$ process versus the H_a : y is an $I(0)$ process. (A time series of order n, written $I(n)$, is a series which must be differenced n times in order to be stationary.) Although this specification does not include a possible time trend, there is an ADF test which tests stationarity given a time trend. This null hypothesis can be tested using a type of t-statistic on β. However, because under the null hypothesis, this test statistic does not converge in distribution to a nicely behaved random variable, special tables of critical values have been constructed through extensive Monte Carlo simulation.[2]

In the panel case, the question is how to combine information on stationarity or non-stationarity for each individual cross-section into a conclusion about the panel as a whole. Assuming that the cross-sections are independent, IPS propose that the best way to combine information is to average the individual ADF t-test statistics and use the following properties on the mean:

$$\bar{z}_{NT} = \frac{\sqrt{N}(\bar{t}_{NT} - E[\bar{t}_{NT}(p,0)])}{\sqrt{Var(\bar{t}_{NT})}} \xrightarrow{d} N(0,1)$$

$\bar{z}_{NT}$ can be compared to critical values for a one-sided $N(0,1)$ distribution. The moments of $\bar{t}_{NT}$ depend on the number of time series observations and the appropriate lag order for each cross section. IPS provide the

[1]Informally, a stationary variable is one which has no tendancy to grow continually over time. A stationary variable has finite variance and an exogenous shock to the series will be "forgotten" as time continues and the series returns to its underlying path.

[2]For a summary of tests and appropriate critical values, see Hamilton (1994) pp. 528-529, pp 762-763 or Fuller (1976) pp. 371, 373.

necessary tables to construct these moments for each individual data set. The selection of the appropriate lag order for the variables here follows the procedure suggested by Campbell and Perron (1991). For the results in this chapter, the cross-sections are assumed independent.

If we find that GDPW and one or both of the variables KAPW and urbanization are non-stationary, then we can test the system for cointegration. The residual-based test for cointegration we use comes from McCoskey and Kao (1998). The test is constructed from the partial sums of the estimated residuals of a regression equation of non-stationary variables. It is a panel data version of the LM statistic proposed by Harris and Inder (1994). The precise form of the test is given:

$$\overline{LM} = \frac{1}{N} \sum_{i=1}^{N} \left(\frac{\frac{1}{T^2} \sum_{t=1}^{T} S_{it}^{+2}}{\widehat{\varpi}_{i1.2}^{2}} \right)$$

where S_{it} is the partial sum of estimated residuals

$$S_{it} = \sum_{j=1}^{t} \widehat{e}_{ij}.$$

The residuals can be estimated either using fully modified Estimation (FM) or dynamic ordinary least squares (DOLS). [3]

Given asymptotic, consistent estimation of the residuals, it can be shown that:

$$LM^* = \sqrt{N} \left(\overline{LM} - \mu_v \right) \xrightarrow{d} N\left(0, \sigma_v^2\right). \tag{5}$$

Thus, an appropriately normalized version of the statistic converges to a normally distributed random variable with mean zero.

Essentially, this test is combining evidence from averaging the LM statistic across the cross-sections. The test is one-sided: large values of LM^* correspond to estimating non-stationary residuals and will result in rejection of the null hypothesis of cointegration (equivalent to rejecting the stationarity of the errors). Rejection of LM^* concludes that the average of the individual LM statistics across the countries in the panel is far away from the mean, μ_v, constructed under the null.

In this limiting distribution, μ_v and σ_v^2 are the mean and variance, respectively, of a complex functional of Brownian motion. These values depend only on the number of regressors. The appropriate values for up to five regressors can be found in McCoskey and Kao (1998).

[3] There is some evidence that the FM method may be more powerful in small data sets but the demands on the data are also greater. Where possible the FM estimation is used and is noted specifically. However where the tested cointegrating relationship contains two regressors, the DOLS method is used including two leads and two lags in the estimation.

3.1.2 Results for Cointegration Among Non-trended Series

In this section, we assume that none of the individual series we include in our model contains a trend. Thus, it is assumed for each series, y_i that $E(\Delta y_{it}) = 0$. This means that each series could contain a non-zero intercept but not a time trend. To test the three series of urbanization, KPW and GDPW for stationarity in our panels of developed and developing countries, we can use the ADF test given in equation 4 to construct the appropriate $\bar{z}_{NT}$.

The $\bar{z}_{NT}$ for this set of pooled results are as follows:

	Urbanization	KPW	GDPW
Group 1	2.8468830	-2.3542323	0.063962916
Group 2	-1.3251332	1.0377193	-0.22716037

As it is a one-sided test, a statistic less than -1.645 would cause rejection of the null of non-stationarity. The only series which would reject the null is capital stock per worker in developing countries. Individual country results are given in Tables 2-3. All results from the panel testing are summarized in Table 1.

This result is quite interesting and underlines the necessity of dividing the countries into two groups. While both groups have GDPW and Urbanization levels which seem to be continually growing over time, only the set of developed countries experiences such growth in capital per worker. This result seems to agree nicely with what we might predict about one of the fundamental differences between developing and developed countries: the ability to accumulate capital.

Given these results on stationarity, the regression equations can be written[4]:

Group 1:

$$\begin{array}{ccccccccc} \ln Y_{it}^* = & \alpha_i & + & \beta_i \ln K_{it}^* & + & \lambda_i \ln U_{it} & + & \varepsilon_{it} \\ I(1) & & & I(0) & & I(1) & & \end{array} \tag{6}$$

[4]The theory of testing for cointegration is applicable only under the assumption that the independent variables themselves are not cointegrated. Therefore, the next step is to test for a cointegrating relationship between the variables $\ln K_{it}^*$ and $\ln U_{it}$. For the regression with Group 1, the variables cannot be cointegrated because the natural log of capital per worker is stationary. However, with Group 2 the two variables may be cointegrated and a residual based test must be done. The following relationship is tested:

$$\ln U_{it} = \psi_i + \delta_i \ln K_{it}^* + \mu_{it}.$$

This test is constructed using μ_v and σ_v^2 equal to .1162 and .0109, respectively, from McCoskey and Kao (1998) for construction of the test with one regressor. The null hypothesis of cointegration between capital per worker and urbanization is rejected for Group 2 with $\overline{LM} = 8.4362$, far away from the one-sided critical value of 1.645. In this case, with one regressor, estimation was done with the fully modified procedure.

Group 2:

$$\begin{array}{lcccccccc} \ln Y_{it}^* = & \alpha_i & + & \beta_i \ln K_{it}^* & + & \lambda_i \ln U_{it} & + & \varepsilon_{it} \\ I(1) & & & I(1) & & I(1) & & \end{array} \tag{7}$$

Given that the regressors are not themselves cointegrated, a cointegrating relationship as specified by equation 6 and equation 7 can be tested.[5]

Because the test for cointegration is based on estimated residuals, the parameter estimates are reported simultaneous to constructing the test statistic. The individual LM test statistics are reported in Tables 4 and 6 and the individual parameter estimates are reported in Tables 5 and 7. Originally the test of the null hypothesis of cointegration, LM, was proposed for use in the literature as the test of the null of no cointegration was thought to have low power. Therefore, it may be useful to check the individual time series results against the individual ADF test statistics for the null of no cointegration. The ADF test of the null of no cointegration is analogous to the ADF test for unit roots from equation (4), except that the test is now based on estimated residuals for the error terms. The critical values of the test depend on the estimation and are no longer the same as those for the unit root test. Using a 5% critical value for the ADF test of the null of no cointegration with two regressors from Phillips and Ouliaris (1990), -3.7576, the null of no cointegration is rejected for only two countries. These individual ADF results are also reported in Tables 4 and 6.

It is clear from the results in Tables 4 and 6 that low power is an issue with both the time series results for the LM and ADF tests for cointegration. In fact in only a few cases can the null be rejected with either test. Thus, country by country we cannot reject either null. The low power of the tests is a major motivation for pooling data into a panel. When we pool out results, for Group 1, the null hypothesis of cointegration cannot be rejected with $LM^* = -5.416$[6].

Consider the parameter estimates for Group 1. As the LM^* test statistic has failed to reject the null hypothesis of cointegration, the vector of estimated coefficients can be interpreted as the potential cointegrating vector of the system. These estimates can be interpreted as long run impacts. Considering the estimated parameters in Table 5, it is encouraging to note, that for most cases, the coefficient β_i, which can be interpreted as the elasticity of output per worker with respect to capital per worker, is positive. In almost 2/3 of the cases, the estimated parameter lies between 0 and 1 which is consistent with the model specification, although 10 of the 16 significant estimates are greater than 1. Only Peru has a significant estimate

[5] For more details on the log transformation in time series analysis, see Banerjee (1994) p.192-199.

[6] μ_v and σ_v^2 equal to .0850 and .0055, respectively, are used as the mean and variance for two regressors and are reported in McCoskey and Kao (1998)

for the elasticity less than 0. It is also interesting to note that exactly half, or fifteen of the thirty countries have negative estimates for λ_i. 15 of the 30 estimates for λ_i are significant with 7 of the 15 less than 0 and 8 greater than 0. A negative λ_i would mean a negative elasticity of output with respect to urbanization. The result is interesting within the context of the debate of whether or not developing countries have become overurbanized.[7]

The results for the testing on Group 2 are similar: the null hypothesis of cointegration cannot be rejected with $LM^* = -4.7427$. Results for individual testing, both LM and ADF test statistics are provided in Table 6 for Group 2. Parameter estimates are provided in Table 7. In this Group, 10 out of the 22 estimates for urbanization are significant with only 3 of those less than 0. For the estimates on KAPW, 13 out of 22 are significant with none of the significant estimates less than 0 and only 4 greater than 1.

Given our production function specification, there is an clearly important link between λ_i, β_i and output per worker. In particular, for countries where $\lambda_i < 0$, there is an added imperative for capital accumulation in order to see growth in output per worker. Starting with the production function

$$Y_{it}^* = A_{it}(U_{it})^{\lambda_i}(K_{it}^{*\beta_i})$$

and holding A_{it} constant, we can take the total differential with respect to U and K^*

$$dY_{it}^* = A_{it}\lambda_i(U_{it})^{\lambda_i - 1}(K_{it}^{*\beta_i})dU + A_{it}(U_{it})^{\lambda_i}\beta_i(K_{it}^{*\beta_i - 1})dK^*.$$

We set $dY_{it}^* = 0$ to find the trade-off between dU and dK^* necessary to hold output constant. It can be shown that

$$dK^* = -(\frac{\lambda_i}{\beta_i}\frac{K^*}{U})dU.$$

It can be seen directly, and is quite intuitive, that larger negative values of λ_i require larger levels of change in capital accumulation per worker for economic growth. Thus for developing countries, overurbanization has a very similar effect as high birth rates in terms of future economic growth. For countries where $\lambda_i > 0$, countries can experience decreases in capital per worker and yet still experience growth in output through the positive effects of urbanization.

[7] If we reject cointegration then we encounter the problem of estimating a spurious regression. As discussed in Granger and Newbold (1974) and Phillips (1986), a spurious regression of two independent non-stationary series will tend to show a significant relationship when none exists. The problem gets worse as the time dimension increases. In the absence of cointegrating relationship, the specification is spurious. A spurious regression has the following characteristics: (a) estimates are not consistent and converge to random variables, not constants; (b) OLS t and F statistics diverge; (c) R^2 may not tend to 0. Thus, caution is suggested when interpreting results from spuriously estimated regressions.

How should one interpret the failure to reject the null hypothesis of cointegration? Statistically speaking, the failure to reject the null means that we cannot rule out a long run relationship between the natural log of RGDPW, KAPW and urbanization levels for either developed or developing countries. This result seems quite promising for further investigation of dynamic urban models.

Although we cannot reject cointegration in the model above, we may want to consider a possible specification problem in our assumption that our series do not contain a time trend. This assumption may be overly restrictive. We address this consideration in the next section.

3.1.3 Results for Cointegration Among Trended Series

In the previous section we assumed that none of the series contained a time trend and found that with this specification cointegration cannot be rejected. In this section, we assume that the series do contain time trends. Including a time trend in the path of a non-stationary can be appealing intuitively. Because the variables are in natural log form, the results for the series which are $I(1)$ are easily interpreted. The designation of $I(1)$ implies that differencing the data once will result in a stationary series. Thus, for example, if $\ln U_{it}$ can be written as:

$$\ln U_{it} = \gamma_i + \ln U_{it-1} + \varsigma_{it}$$

where

$$\varsigma_{it} \sim (0, \sigma_i^2)$$

or, equivalently

$$\Delta \ln U_{it} = \gamma_i + \varsigma_{it}$$

In other words, $\Delta \ln U_{it}$ describes the growth rate of urbanization and this growth rate is stationary and varies around a constant mean, γ_i. In this case, γ_i represents our time trend.

The first adjustment we must make under this new assumption is to revisit the IPS test, and retest GDPW, this time including a time trend in the test for stationarity. The rationale is as follows: in essence, if we assume that each series includes a time trend, then these trends asymptotically dominate and the cointegration regression is reduced to a test for non-stationarity including a time trend. Thus the cointegrating regression between the three series collapses into a test for non-stationarity on GDPW. [8] The ADF specification can be written as follows:

[8] For more details see Hamilton pp. 596-597.

$$\Delta y_t = \alpha + \beta y_{t-1} + \delta t + \Sigma_{j=1}^{p_i} \gamma_j \Delta y_{t-j} + v_t. \tag{8}$$

If each series is non-stationary about a trend, then the trend itself will become more important in the long run relationship than variations about the trend. By collapsing the cointegration regression to a test of non-stationarity on a series it becomes clear however, that interpretation of the relationship is difficult. In this case, even if GDPW is stationary about a trend, the results cannot tell us more about where the trend itself is coming from. We gain no information about the potential importance of either urbanization or KAPW. The results from the testing given in Table 1 show that for Groups 1 and 2 respectively, the $\bar{z}_{NT}$ are 3.6194 and -1.4011, showing that, under these assumptions, we cannot reject the null hypothesis of non-stationarity.

3.2 Cross-Section Results and Average Effects

3.2.1 Testing for Average Effects

The results from the above cointegration analysis should be considered in contrast to more traditional cross-section results. In fact, the two types of studies seem to be answering very different questions. The cross section studies traditionally attempt to find average long run effects rather than examining specific paths of different countries. In Pesaran and Smith (1995) two methods are given to consistently estimate these long run averages in the presence of cointegrating relationships.

The first method is given as simply taking the average across the individual parameter estimates for each cross section. Thus

$$\bar{\beta} = \sum_{i=1}^{N} \beta_i.$$

The second suggested method involves estimating a cross section relationship between the averages, across time, of the groups. Thus the estimated regression is defined as

$$\bar{y}_i^* = \alpha + \beta \bar{k}_i^* + \lambda \bar{u}_i + \varepsilon_i$$

where

$$\bar{y}_i^* = \sum_{t=1}^{T} \ln y_{it}^*.$$

All of the variables are again in logs. In this specification, the estimates will be consistent and unbiased. However the usual standard errors are not valid. Pesaran and Smith suggest White's heteroskedasticity-consistent standard errors. It should be noted that using the cross-section approach to estimate average effects has one major disadvantage over the dynamic approach: in this approach the regressors are assumed to be strictly exogenous. Both the dynamic and cross-section approaches require independence across the cross-sections for the asymptotic results to hold.

Pesaran and Smith do provide an important caution for those studies where very short time periods are used to estimate average effects (such as the strict cross-section approach), such estimations are likely to be biased or inconsistent. Thus, even in this "cross-section" approach, the time dimension of the panel is crucial.

3.2.2 Results for Average Effects

Average of the estimated parameters Following the guidelines by Pesaran and Smith, our first method of averaging the individual estimated coefficients for Urbanization and KPW across the cross sections yields the following results:

	Group 1	Group 2
Urbanization	-0.4760	1.2835
	(1.2856)	(1.0291)
KAPW	0.7828	0.6096
	(0.1442)	(0.1181)

The standard errors reported are calculated under the assumption that the cross sections are independent and using the usual properties on variances of the average of independent random variables, i.e. $Var(\frac{1}{n}\Sigma_{i=1}^{n}X_i) = \frac{1}{n^2}\Sigma_{i=1}^{n}Var(X_i)$.

At first glance it is disappointing to realize that for neither group is the coefficient on urbanization further than two standard deviations away from 0, however when considering the estimates on which this is based such an inconclusive result is predictable. When the original estimates were done in both groups the sample was almost split with both positive and negative coefficients on urbanization. The result on KAPW is much clearer-in both cases the coefficient is positive and at least two standard deviations away from zero.

Determining the exact form of the distribution of the average of n t-statistics is a bit unclear in the case of Group 2 with only 22 observations. However since Group 1 has 30 cross-sections we could approximate the distribution using a form of the central limit theorem. For more details see Dudewicz (1988) p. 322 on Lindeberg's conditional central limit theorem.

Average Cross-Section Results Using the second method suggested and constructing averages across time and using OLS, we obtain the following results:

	Group 1	Group 2
Urbanization	0.8954	0.5519
	(0.1464)	(0.2020)
	(0.9933)	(7.2275)
KAPW	0.1668	0.5479
	(0.0597)	(0.0860)
	(0.2717)	(2.9682)

The first set of standard errors reported are those from the original OLS estimation; the second set of standard errors reported are calculated from White's heteroskedasticity consistent estimator variance-covariance matrix.

The results from this estimation, when taken with the second set of standard errors coincides strongly with the previous results with regards to urbanization. In neither case is urbanization significantly different from 0. However, in this estimation, the results on KAPW are also inclusive.

It is clear that using White's heteroskedasticity consistent estimator corrections for the standard errors makes an enormous difference in the interpretation of the results, especially in the case of Group 2. The OLS standard errors would cause us to conclude that all estimates are positive and significantly different from 0 based on the estimates for standard errors. It is interesting to note that despite the inconclusive results on the parameters, the estimated R^2 for Group1 is 0.848 and Group 2 0.787.

When taken as a whole, these results seem to support that average effects of the elasticity of capital per worker with respect to output to worker positive. This result is nice but not very groundbreaking. With regard to urbanization, the results are much less conclusive. In fact based on the inability of the estimates to determine even the sign on the average effect of the elasticity of urbanization we conclude that attempting to estimate such an average effect may be misguided-based on our dynamic studies it seems clear that the impact of urbanization varies greatly across the cross-sections. Such an individualized impact, which may depend crucially on internal economic and political structure, can be best captured in the dynamic, heterogeneous approach.

4 Conclusion

Urban economists have been anxious to link output and measures of urbanization. Cities form, it is assumed, in response to market forces in production. In this essay an attempt is made to pin down the exact relationship between urbanization and output over time using results from the time series literature and non-stationary panel data literature. A traditional constant returns to scale Cobb Douglas production function is specified with urbanization as a shift factor. The results show clearly that this specification cannot be rejected and may be useful in understanding long run growth. However, even if urbanization is crucial to growth, our results show that the impact of urbanization varies greatly across countries and therefore attempts to identify or even determine the sign of long run effects may be misguided.

There are other important results from this study as well. Testing presented here shows that the natural logs of urbanization and GDP per worker are non-stationary for the group of developing countries and for developed countries, the natural logs of GDP per worker, capital per worker and urbanization are all non-stationary. Serious studies of the dynamic relationship between growth in GDP and urbanization should take heed of these results; otherwise, estimation may be spurious. In addition, using results from Pesaran and Smith, it should also be mentioned that estimating average long run effects with a simple cross-section may be biased or inconsistent. It is clear that using results from the time series literature and dynamic panel literature may greatly facilitate our understanding of the intersection of urbanization and growth.

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Table 1: Panel Data Test Results

IPS TEST			
Without time trend			
Group 1			
	Urban	2.8469	Fail to reject
	KPW	-2.3542	Reject at .05
	GDPW	0.064	Fail to reject
Group 2			
	Urban	-1.3251	Fail to reject
	KPW	1.0377	Fail to reject
	GDPW	-0.2272	Fail to reject
With a time trend			
Group 1			
	GDPW	3.6194	Fail to reject
Group 2			
	GDPW	-1.4011	Fail to reject
PANEL LM TEST			
Group 1 (GDPW, KAPW, Urban)			
		-5.4516	Fail to reject
Group 2 (GDPW, KAPW, Urban)			
		-4.7427	Fail to reject
(KAPW, Urban)			
		8.4362	Reject at .01

Table 2: Individual ADF t-stats: Group 1

	Urbanization	KPW	GDPW
Argentina	-2.3151	-2.6326*	-2.2582
Bolivia	0.3726	-2.1135	-2.2479
Chile	-3.1927**	-2.0004	-2.8598*
Columbia	-3.3612**	-2.2518	-2.3654
Cote D'Ivoire	-2.4930	-1.6646	-1.9082
Dominican Republic	-1.9182	-1.5129	-1.7880
Ecuador	-0.2390	-2.0324	-1.4832
Guatemala	-1.5439	-1.9680	-2.2497
Honduras	-3.9563**	-2.4028	-1.9476
India	1.1138	-3.1971**	3.2032
Iran	-2.1397	-1.6023	-1.4604
Jamaica	-0.5695	-2.3044	-2.3326
Kenya	-0.8518	-0.5651	-1.9688
Madagascar	2.0545	-2.8638**	-0.1857
Malawi	-0.2644	-2.0254	-1.7129
Mexico	-3.8412**	-1.7475	-2.4125
Morrocco	-1.4988	-2.1068	-1.8636
Nigeria	-2.9981**	-1.7269	-2.1622
Panama	0.4642	-2.0249	-2.1092
Paraguay	0.4263	-1.4499	-1.5993
Peru	-1.4349	-2.0865	-0.6427
Phillippines	0.1637	-1.9132	-1.6741
Sierra Leone	-0.7087	-2.6404*	-1.9253
Sri Lanka	-2.9452**	-0.5868	0.0933
Syria	-0.3409	-0.9834	-2.4648
Thailand	0.1818	-1.7644	0.2119
Turkey	-1.6137	-2.0440	-2.0339
Venezuela	-1.7234	-1.7668	1.4048
Zambia	-1.6314	-0.2945	-0.2561
Zimbabwe	9.1981	-1.0456	-2.0440

Notes:
(a) Lag Orders calculated for each country according to Campell and Perron (1991).
(b) Critical values at the 5 (**) and 10 (*) percent level: -2.93701, -2.61518 from GAUSS.

Table 3: Individual ADF t-stats: Group 2

	Urbanization	KPW	GDPW
Australia	-3.4885**	0.7459	-1.2794
Austria	0.4357	-2.3094	-2.8299*
Belgium	0.2149	-1.8410	-2.3667
Canada	-2.8796*	1.6013	-0.0469
Denmark	-2.6047	-2.6765*	-1.2061
Finland	-2.6380*	-1.7928	-0.9433
France	-3.0712**	-1.4371	-2.385
Federal Republic Germany	-3.1436**	-2.6543*	-3.0203**
Greece	-0.8825	-3.5350**	-3.0626**
Ireland	-0.0853	-2.6753*	-1.7607
Italy	-0.5815	-3.8475**	-2.4736
Japan	-2.6685*	-0.9361	-2.1065
Korea	-1.8084	-1.6017	-0.3806
Luxembourg	-2.4912	1.7426	-0.6712
Netherlands	-2.2976	1.7426	-3.1028**
New Zealand	-2.7107*	-1.4798	-1.1726
Norway	-2.8009*	0.9531	-0.4796
Spain	-2.0595	-1.2617	-1.5343
Sweden	-3.5318**	-0.5164	-0.3615
Switzerland	2.1977	-2.1674	-1.4442
United Kingdom	-1.5690	-1.5579	-0.0095
USA	0.8579	-0.5066	-0.4240

Notes:
(a) Lag Orders calculated for each country according to Campbell and Perron (1991).
(b) Critical values at the 5 (**) and 10 (*) percent level: -2.93701, -2.61518 from GAUSS.

Table 4: Individual LM and ADF Cointegration Test Results: Group 1

	LM TEST	ADF TEST
Argentina	0.0165	-3.6790*
Bolivia	0.0060	-3.0236
Chile	0.0160	-3.1209
Columbia	0.0164	-2.4075
Cote D'Ivoire	0.0079	-2.2396
Dominican Republic	0.0190	-1.7538
Ecuador	0.0153	-3.0758
Guatemala	0.0082	-2.1812
Honduras	0.0074	-2.0230
India	0.0075	-1.2202
Iran	0.0102	-2.2088
Jamaica	0.0098	-1.4880
Kenya	0.0084	-3.9387**
Madagascar	0.0121	-3.3935
Malawi	0.0073	-3.5129*
Mexico	0.0204	-2.9623
Morrocco	0.0087	-2.6337
Nigeria	0.0130	-1.8776
Panama	0.0085	-2.1716
Paraguay	0.0053	-3.5054*
Peru	0.0158	-1.4686
Phillippines	0.0295	-1.8755
Sierra Leone	0.0058	-3.2872
Sri Lanka	0.0098	-5.2063**
Syria	0.0087	-0.4463
Thailand	0.0096	-2.6791
Turkey	0.0079	-1.8103
Venezuela	0.0069	-0.6229
Zambia	0.0093	-2.9741
Zimbabwe	0.0084	-2.6122

Notes:
(a) Lag Orders calculated for each country according to Campell and Perron (1991).
(b) Critical values at the 5 (**) and 10 (*) percent level for the LM Test: .2177 and .1617 from Harris and Inder (1994).
(c) Critical values at the 5 (**) and 10 (*) percent level for the ADF Test: -3.7675 and -3.4494 from Phillips and Ouliaris (1990).

Table 5: Parameter Estimates (Potential Cointegrating Vector): Group 1

	Urbanization	KPW		Urbanization	KPW
Argentina	-11.6618	0.8650	Peru	-0.1646	-2.2677**
	(33.0934)	(2.0959)		(1.0598)	(0.7283)
Bolivia	1.1361	0.5123**	Phillipines	0.8339	0.7503
	(0.9229)	(.0601)		(2.6393)	(1.6334)
Chile	-1.2318	2.4682**	Sierra Leone	-3.5124**	1.5436**
	(4.0886)	(1.0601)		(1.4049)	(0.6619)
Columbia	11.7858	0.1485	Sri Lanka	-9.4687**	0.4426
	(11.7483)	(0.9606)		(3.3558)	(0.4143)
Cote D'Ivoire	-0.0525	0.7477	Syria	-0.7261	1.0406**
	(1.3692)	(0.5222)		(2.0656)	(0.4408)
Dominican Republic	-5.5952	0.9790	Thailand	0.6625	0.3681
	(12.8775)	(1.2809)		(0.9224)	(0.4324)
Ecuador	-4.9294**	2.4941**	Turkey	1.9848**	0.4513
	(1.7381)	(0.7626)		(0.7673)	(0.3390)
Guatemala	1.2456**	0.6837**	Venezuela	-5.4436**	2.3985**
	(0.3127)	(0.1102)		(0.7134)	(0.3962)
Honduras	4.5996**	0.6486**	Zambia	-0.4664	0.4665
	(0.8955)	(0.0615)		(1.3495)	(0.4338)
India	2.2072**	-0.4081	Zimbabwe	4.7156**	2.7276**
	(0.6048)	(0.3226)		(1.7077)	(1.2712)
Iran	6.7274	-0.6880			
	(4.8111)	(1.1036)			
Jamaica	1.2617	1.1434**			
	(1.0105)	(0.2734)			
Kenya	0.4166*	0.0274			
	(0.2285)	(0.1043)			
Madagascar	-0.2229*	0.2239*			
	(0.1296)	(0.1246)			
Malawi	0.6876**	0.1084			
	(0.2152)	(0.0848)			
Mexico	-7.0563**	0.6170**			
	(1.9559)	(0.1167)			
Morrocco	2.3444**	-0.4562			
	(0.6703)	(0.3049)			
Nigeria	-1.4528	2.6991**			
	(1.4437)	(1.3526)			
Panama	-0.9437	1.6904**			
	(0.7731)	(0.2422)			
Paraguay	-1.9483*	1.0581**			
	(1.1137)	(0.2847)			

Notes:
(a) Standard errors are reported in parantheses; significant at 10(*) and 5 (**) percent.
(b) Model estimated with intercept in COINT 2.0.

Table 6: Individual LM and ADF Cointegration Test Results: Group 2

	LM TEST	ADF TEST
Australia	0.0096	-1.8312
Austria	0.0105	-2.0507
Belgium	0.0055	-1.4411
Canada	0.0158	-2.3939
Denmark	0.0083	-2.3568
Finland	0.0098	-2.7820
France	0.0127	-2.3878
Federal Republic Germany	0.0188	-2.9037
Greece	0.0156	-2.7075
Ireland	0.0050	-2.9789
Italy	0.0124	-3.3007
Japan	0.0059	-2.8135
Korea	0.0070	-1.8898
Luxembourg	0.0102	-2.7081
Netherlands	0.0099	-3.4408
New Zealand	0.0108	-2.6674
Norway	0.0079	-1.9031
Spain	0.0079	-1.4422
Sweden	0.0110	-1.5045
Switzerland	0.0052	-2.9951
United Kingdom	0.0126	-2.9047
USA	0.0077	-3.8035**

Notes:
(a) Lag Orders calculated for each country according to Campbell and Perron (1991).
(b) Critical values at the 5 (**) and 10 (*) percent level for the LM Test: .2177 and .1617 from Harris and Inder (1994).
(c) Critical Values at the 5 (**) and 10 (*) percent level for the ADF Test: -3.7675 and -3.4494 from Phillips and Ouliaris (1990).

Table 7: Parameter Estimates (Potential Cointegrating Vector): Group 2

	Urbanization	KPW		Urbanization	KPW
Australia	6.4541	0.8745**	Sweden	8.0661**	0.0985
	(10.9925)	(0.3603)		(3.8855)	(2.0760)
Austria	-2.4958	0.7775**	Switzerland	-0.5293	0.4914**
	(1.6129)	(0.3295)		(1.3298)	(0.2158)
Belgium	-1.570	0.8314**	United Kingdom	2.0313	0.4612**
	(2.7750)	(0.777)		(5.3103)	(0.1927)
Canada	19.1272**	0.1248	USA	-9.6019	0.2910
	(8.4707)	(0.1919)		(15.0053)	(0.3757)
Denmark	5.3582**	-0.0481			
	(1.8584)	(0.2114)			
Finland	0 .6886**	0.5484**			
	(0.1559)	(0.0507)			
France	1.3130	0.3278			
	(1.8539)	(0.2596)			
FRG	-13.2439**	0.5286**			
	(3.6846)	(0.0855)			
Greece	0.5740	0.3298			
	(0.6916)	(0.3358)			
Ireland	5.1814**	-0.1106			
	(2.1306)	(0.2981)			
Italy	-7.8037**	1.9489**			
	(1.1566)	(0.1560)			
Japan	-0.4680	0.6040**			
	(0.5565)	(0.0284)			
Korea	0.1000	0.9230**			
	(1.0272)	(0.3473)			
Luxembourg	1.0607	1.2684**			
	(1.3682)	(0.6262)			
Netherlands	9.2620**	-0.0537			
	(0.7665)	(0.0644)			
New Zealand	8.2611**	0.0065			
	(2.5152)	(0.1582)			
Norway	-0.3109	2.0965**			
	(1.2435)	(0.6119)			
Spain	-3.2181**	1.0908**			
	(0.9668)	(0.2593)			

Notes: (a) Standard errors are reported in parantheses; significant at 10 (*) and 5 (**) percent.
(b) Model estimated with intercept in COINT 2.0.