GLOBALISATION AND WAGE DIFFERENTIALS:

A SPATIAL ANALYSIS

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ABSTRACT

Fujita, Krugman and Venables (FKV) develop a model in which international wage differentials encourage industrial mobility because the advantages provided by strong input-output linkages within high cost countries are offset by the benefits of locating in low wage economies. In this paper we argue that globalization has another important dimension. Shocks may originate in a single country but, with modern transportation and telecommunications media, these shocks spread quickly and with multiple shocks a complex process of spillovers effects will be generated. We assess these forces in an analysis of international wage convergence, identifying a non-linear relationship and showing that not all countries will converge. Given that the FKV model omits many of the causes of such non-convergence, our evidence further demonstrates that the FKV model could usefully be extended.

JEL : O18, O47, R12, R15, C21
Keywords - Cross-Sectional Models, Spatial Models, Econometric Methods, Single Equation Models, Mathematical and Quantitative Methods

INTRODUCTION

We can successfully characterize globalization, at least in part, as the process that creates economic outcomes, in our case dynamics involving average wage level differences between countries, that result from a mechanism producing industrial mobility across international frontiers. The assumption is that the movement of industrial firms is precipitated by international wage differentials such that the advantage provided by strong input-output linkages within high cost countries are more than offset by the benefits of locating in low wage economies, and this process of movement sets in motion dynamical changes in the relative per capita wealth of different countries. This type of process underlies the formal model, given by Fujita, Krugman and Venables (1999), or hereafter FKV, that provides the theoretical background to what is essentially an applied econometrics paper. However, there is another dimension to globalization that we would like to highlight at this juncture, which is the role of shocks in the global economy. Shocks, which are defined as completely unpredictable events that affect the level of wages, when originating in a single country, are much less confined to that country than was the case prior to the advent of modern transportation and telecommunications media, so that shocks spread from their source and almost instantaneously impact on the economies of other countries. Of course shocks occur simultaneously in all countries, so that a complex process of shock spillovers between countries ensues. This type of simultaneous dissemination of shocks is not part of the formal model described below, but it is an essential part of the empirical model which is the focus of this paper.

THEORETICAL BACKGROUND

There are a number of theories that we could use as a motivation for our empirical model. We focus on a model provided by Fujita, Krugman and Venables (1999), although it does not provide an exact explanation of all our empirical results, but nevertheless it gives some formal background to the empirical model we estimate. In FKV, as a broad simplification, in the specific case of multiple industries and many countries, a model is presented which relies on autonomously increasing technology driving growth, with multiple sectors and input-output relationships with intermediates giving strengthening forward and backward linkages with industry and increasing returns to agglomeration, causing rising wages and capital mobility and the dynamics leading to a long-run equilibrium involving several countries. The model is neatly summarized by a three-country simulation, given as Fig 15.3 in FKV, which the basis of imputed reduced-form outcomes that motivates our subsequent empirical analysis. The main thesis in their model is that as the level of technology increases, countries sequentially move from a state of poverty to a level of real wages on a par with richer countries. Their sequential dynamics show that the growth of wages is nonlinearly correlated with the level of wages so that at a given point in time (eg through stage II in Fig. 15.3) different countries have different wage growth and levels. As a given country goes through stages from low to high wage levels wage growth is low or negative then high then at the highest wage level again becomes negative, and countries converge to the same wage level at a stable equilibrium. The processes leading to this ordering are explained elegantly by FKV and there is no need to replicate their detailed explanation in this short paper. But we only have simulations involving 3 countries, although there are multiple 'observations' of these 3 countries through time, and so it appears reasonable to characterize this relationship as a non-monotonic function. Obtaining a precise functional form for such a relationship would have the advantage of allowing us to read off what the wage growth (change) will be at any level of wages, which is what is subsequently attempted in the empirical section of the paper. From cross-sectional data we can estimate a quadratic function relating wage change to wage level at a 'point' in time that is consistent with outcomes which might be inferred from the dynamics traced in Figure 15.3.A quadratic (or similar) function implies negative change at low and high wage levels, large positive changes at intermediate wage levels, and this is also apparent in FKV Fig 15.3.

Figure 1 near here, title ‘The FKV model’

Despite negative wage changes at low wage levels, the situation rectifies itself under FKV, and the lowest wage countries converge to an equilibrium. This is because 'at some point the wage gap becomes too large to be sustainable’, and ‘country 3 wages start to catch up with those in 1 and 2' (FKV, page 273). In FKV sufficiently low wages will prove attractive to mobile capital. However, FKV (page 278) add words of caution, 'we do not really believe that this model captures all or even most of the forces actually driving development'. In FKV sufficiently low wages attract mobile capital, but in reality there are other factors excluded from FKV which mean that for some countries wages will never be low enough. So FKV is only a partial account of reality and is alone not adequate if we want to describe what actually happens. Although the seminal book by FKV should be consulted for a complete and authoritative explanation of their model, let us try to explain more fully why their model fails to detect the non-convergence property identified in the empirics. The big assumption that we wish to question is that all poor countries somehow are able to attract investment that spills over from richer countries that have become too expensive, with too high wages, so that despite the input-output linkages developed in the richer countries, it become feasible and attractive to go offshore to a cheaper production site. This might be true for some, but there is an obvious limitation to this argument, because it omits the many other factors that enter into a location decision and which for some countries may mean that spillover is never possible. For

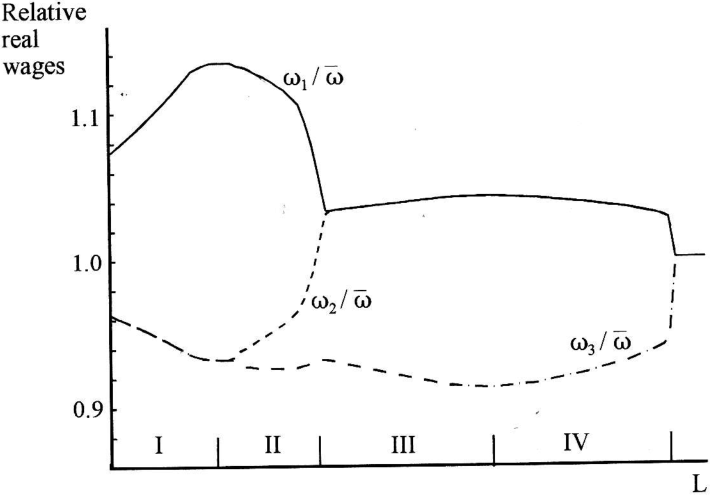

Figure 15.3
Relative real wages, multicountry model

example, although a country may be ostensibly cheaper, it may have poor institutions, corruption, a poor climate, an underdeveloped social infrastructure, political instability, and so on, that are so permanently embodied in its economic, environmental and social fabric that that it may never receive enough inflow of capital from richer countries to allow wage rates to rise above the very low level. Whilst it is difficult in practice to control for the immeasurable institutional factors specifically affecting individual countries, broad quantitative patterns will emerge and these will be distinctly different from those predicted by FKV. Rather than some poor countries growing rapidly and converging on the equilibrium wage level, as in FKV, they remain rooted at the bottom of the wage league table. Because of the causal partiality embodied in FKV, we cannot take this as a serious prediction of actual dynamics.

Taking the observed empirics at face value, we can read off from the quadratic function the wage change associated with a wage level, and the implication of negative wage change at low wage levels means falling wage levels over time, but there is nothing strong enough to pull the lowest wage countries back to the equilibrium level to which the majority of countries are converging, because of the other factors that impede mobility of industry. Thus the simple quadratic relationship between wage level and wage change, which is evident once we have allowed for the presence of spatially disseminating shock effects on wage levels, and which are manifest as spatially autocorrelated residuals, does not imply complete convergence by all countries. Rather it points to convergence by the majority of countries, but a handful of countries are relegated to a long-term steady state in which only subsistence wages are paid. It does appear therefore that the predictions of the FKV model are out of step with the dynamic implications of the empirical reality that has been identified. So while the mechanism of FKV does do a good job describing the convergence of the majority of countries to an equilibrium, the FKV model process does not apply to all countries. The dynamics of some countries do not seem to be well described by FKV because of the partial nature of the theory. Taking the quadratic at face value, the simple mechanism where we have wage change leading to a new level then a different wage change at that level leading to a new level and so on does describe dynamic paths that would seem to correspond to what we might see from an FKV model, but from an FKV model if that model were to be adapted so as to block the convergence of the lowest wage countries.

EMPIRICAL RESULTS

A quadratic function does seem to accord with what might be imagined to be the manifestation, at a ‘point’ in time, of the sequential process described in FKV, so that the change in wage level Δw is nonlinearly related to the wage level $w_0 \geq 0$ in a way that partly reflects the dynamics arising from the formal model discussed in the preceding section. This requires that the parameters in equation (1) are appropriately signed, hence

$$\begin{aligned} &\Delta w = a{w_0}^2 + bw_0 + c + \varepsilon = Xf + \varepsilon \\ &\varepsilon \sim N(0, \sigma^2) \end{aligned} \qquad (1)$$

In equation (1), the parameters *a* and *b* quantify the responsiveness of Δw to exogenous regressors w_0^2 and w_0 respectively, with c denoting a constant term. The term ε represents shocks or innovations which at this juncture are country-specific with no assumption of spillover across international frontiers. In matrix form, *X* is an n by 3 matrix with columns equal to w_0^2, w_0 and a vector of ones, and *f* is the 3 by 1 vector of parameters. To create the concave function that describes our interpretation of the formal model outcomes, the econometric model given as (1) should generate significant regression coefficients with *a<0* and *b>0*. As explained below, we confirm these hypotheses, but only provided that we extend the model specification to allow shock-effects to transmit internationally.

The estimation that follows is based on a sample of n = 98 countries[1], using data from Penn World Tables Version 6.1 (October 2002), with real GDP per worker measured from 1970 to 2000, in 1996 prices. The start date of 1970 was selected because it just precedes the second contemporary wave of globalisation. The results from the estimation of Equation 1 are recorded in Table 1. The initial indication from this table is that there is no perceptible quadratic relationship between Δw and $w_0 = w_{1970}$.

Table 1

OLS estimates of Equation (12)

Parameter	Estimate	t ratio
$\hat{c}$	-997.0	-0.48
$\hat{b}$	1.022	3.17
$\hat{a}$	-0.00001329	-1.55
σ	10011.0	
log likelihood	-1040.2758	
R^2	0.2912	

The spillover of shocks across international boundaries would be observed as spatially autocorrelated residuals generated by a model from which such spillover effects were excluded, with the spillovers typically being stronger when countries are in some sense closer to each other. Closeness may not be entirely captured by geographical distance, and we can envisage non-geographical spaces (as for instance in the industrial organization literature where firms may be positioned in a multidimensional product space), but since the cost of geographical separation does seem to increase with geographical distance, and large distances may weaken to magnitude of spillovers between countries that are remote from each other, in the current context it does seem appropriate to focus on geographical distance as the principal determinant of the nature and magnitude of shock-effect spillovers. This is supported by the residuals produced as a result of the estimation of equation (1), which indicate that significant residual spatial autocorrelation extends up to 2000 miles, and it falls to zero between 3000 and 4000 miles. In the analysis that follows, we use a cut-off distance of 3,500 beyond which it is assumed that there is no real long-distance residual spatial autocorrelation. The significant long-distance negative autocorrelation is a logical outcome of significant short-distance positive autocorrelation. While we have attributed this to spillovers of shocks between 'neighbouring' countries, residual autocorrelation could also be due to omitted spatially autocorrelated variables. However, this would lead our model specification too far away from its theoretical provenance, so we assume that shock spillovers are what are occurring.

The estimates produced by equation (1) do not correspond to our presumptions about how the theoretical mechanism will be manifest, as a quadratic relationship, because the estimate of the parameter on w_0^2 is small and insignificant. We consequently adapt this model to incorporate the missing element, the spillover of shocks to wage levels across international boundaries, to arrive at our preferred model, equation (2). In considering globalisation, it is impossible to ignore the fact that shocks to wages and productivity are transmitted worldwide: a shock to one economy is also

[1] The entire set of countries is listed in Appendix A.

invariably a shock to (all) other countries. We model this aspect as simultaneous interdependence between economies using the so-called spatial error model (see Anselin, 1988), so that:

$$\begin{aligned} \Delta w &= Xf + \xi \\ \xi &= \rho W \xi + \varepsilon \\ \varepsilon &\sim N(0, \sigma^2 I) \end{aligned} \qquad (2)$$

In equation (2), we see the presence of *W* which is an n-by-n matrix defining network interconnectivity between countries, and it is possible to show that since we have assumed an autoregressive error process, shocks transmit to all countries without exception, although with differing magnitudes. In contrast, a moving average spatial error process would give shocks a much more spatially restricted footprint. The simplest possible structure for *W* is as a set of ones and zeros, with ones defining contiguous countries and zeros defining other non-contiguous countries. This seems however to be unnecessarily restrictive, although we could elaborate this by making the *W* cells values equal to some continuous function of distance. An alternative to the use of distances would be to base the *W* matrix cell values on international trade data and assume, not unreasonably it would appear, that shock-effects are proportional to the trade links between countries. Trade data has been used in the past, for instance as an indicator of the intensity of R&D spillovers between OECD countries (Coe and Helpman, 1995, Verspagen 1997). However, there are some difficulties with this approach. In the case of a sample of countries that includes underdeveloped countries, obtaining comprehensive and accurate trade data is not easy. Also, trade volumes and directions vary substantially over time, and therefore to convert these into a viable *W* matrix format would require some considerable simplification and numerous assumptions, which may be hard to justify, particularly as the asymptotics underlying estimation assume that *W* is a non-stochastic matrix of known constants (see for example Kelejian and Prucha, 1999).

The chosen option is to examine in more detail the OLS residuals of model (1), which does not contain any spatial interaction effects, using the residual correlogram to suggest the range of distances over which the spatial effects may extend and the shape of the distance decay function. A number of alternative measures of spatial autocorrelation are feasible. Here we employ three: Moran's I, the standardized value[2] (Z) of Moran's I, and the correlation coefficient r (the product moment correlation between residuals and their spatial lags). We use 10 distance bands and assign 1 or zero to the weighting matrix for Moran's I according to whether country pairs fall within each distance band. Thus the spatial lag for a given distance band is the matrix product of the vector of residuals and the appropriate weighting matrix. The outcome is given in Table 2.

[2] Deviation from expectation under the null in units of standard deviation.

Table 2

Spatial correlogram based on residuals from Equation (12)

Band	Mean distance	Z	I	r
1	750	6.423	2.0104	0.3629
2	1898	3.899	1.4578	0.3500
3	3141	0.583	0.1200	0.0258
4	4388	-0.444	-0.3481	-0.0564
5	5609	0.829	0.2639	0.0424
6	6858	-1.525	-0.7518	-0.1662
7	8065	-0.765	-0.3468	-0.0713
8	9324	-3.990	-1.0784	-0.3098
9	10552	-4.649	-1.0940	-0.3512
10	11741	-8.002	-1.2330	-0.4554

In order to define *W* for equation (2), a simple transformation from distance to 'correlation' is used, given by

$$W_{ij} = \left(1 - \frac{d_{ij}^G}{d_{\max}^G}\right)^{\pi} \qquad (3)$$

In equation (3), d_{ij}^G is the great circle distance between countries i and j, with the maximum geographical distance beyond which covariances fall to zero given by $d_{\max}^G$, with $\pi \geq 1$ and $d_{ij}^G \geq 0$. When $\pi = 1$ this is the Bartlett kernel (see Phillips, Sun and Jin, 2003), but π is chosen by minimising the sum of the squared differences between the observed values of r (up to $d_{\max}^G$ = 3500 miles) and the corresponding values of $W(\pi)$. The outcome is that π =2.56650.

Table 3 shows the results of estimating equation (2) via maximum likelihood (ML) and by GMM using this *W* matrix specification. ML estimation of the so-called spatial error model is a standard procedure in spatial econometrics and is well documented in the literature (see for instance Cliff and Ord (1981), Upton and Fingleton (1985), Anselin (1988), Haining (1990). GMM follows Kelejian and Prucha (1999), using a feasible generalized least squares estimator. This has the advantage of not assuming normality for the error distribution. The results are very similar to those obtained via ML, suggesting that the normality assumption is tenable.

Table 3

ML and GMM estimates of equation (13)

	ML	*GMM*
$\hat{c}$	1234.68512814	1619.41933802
t ratio	0.45	0.57
$\hat{b}$	0.95121259	0.94104170
t ratio	2.86	2.81
$\hat{a}$	-0.00001831	-0.00001844
t ratio	-2.23	-2.24
$\hat{\rho}$	0.083	0.0899792
t ratio	7.612	…
$\hat{\sigma}$	8866.870169	8822.98
log likelihood	-1031.8235	…

The most notable feature of these estimates is that the modeling of the spatial error process appreciably improves the level of fit, and allows the non-rejection of the theoretical hypotheses associated with the quadratic function, i.e. $a < 0$ and $b > 0$. The estimated value 0.0899792 obtained via GMM is significant when referred to its Bootstrap distribution, obtained by resampling with replacement the residuals. The Bootstrap estimate is -0.003285 and the Bootstrap variance is 0.002692. The estimate ranks first in the Bootstrap distribution given by Figure 1. The structure of W has implications for the estimate of ρ, which under ML is automatically constrained within upper or lower bounds given by the inverse of its maximum and minimum eigenvalues. In order to satisfy the constraint, which ensures a stable autoregressive error process, the likelihood function includes a term that acts as a penalty or weighting function. This has the effect that the likelihood, which is based on a normality assumption, diminishes sharply as ρ approaches its upper or lower bound. The GMM estimate also falls within the bounds, since the large eigenvalues of W is equal to 10.020.

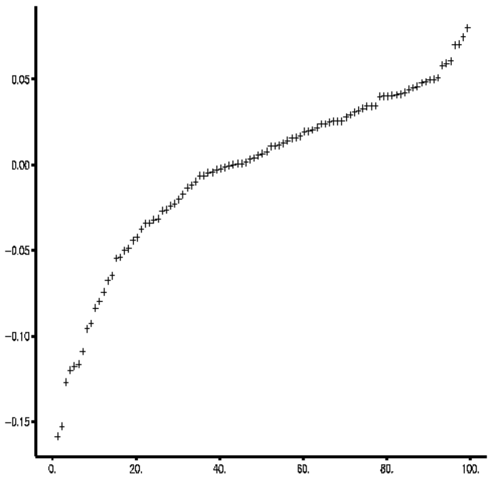

FIG 1 Bootstrap Distribution for the GMM estimate $\hat{\rho}$

DYNAMIC IMPLICATIONS OF ESTIMATED MODEL

As explained above, in assessing the long-run implications for globalisation, our starting point is a quadratic function, as depicted in Figure 2. Figure 2 illustrates graphically that there is a solution to the quadratic with two roots (which would be coincident if $\hat{b}^2 = 4\hat{c}\hat{a}$), since $\hat{a} \neq 0$ and $0 \leq \hat{b}^2 - 4\hat{a}\hat{c}$. Using the ML estimates from Table 3 and solving for the roots using:

$$x_{L,U} = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a} \qquad (4)$$

gives the points, ($\hat{x}_L$ = -1267 ,0) and ($\hat{x}_U$ =53216 ,0).

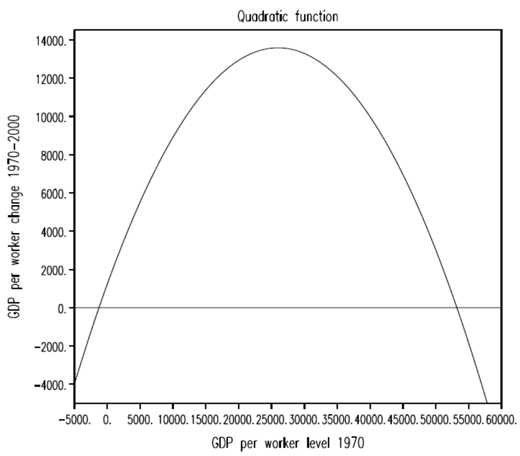

FIG 2 Quadratic Wage Function

On initial inspection, the long-run dynamics implied by the model are that each country will gravitate to the stable upper root, as shown by Figure 3. Thus at this juncture the empirical model produces similar outcomes to the theoretical model described earlier, and although there are no high wage level countries which experience falling wages levels as envisaged in theory, this is a feature of the data to hand rather than a constraint imposed by the quadratic function.

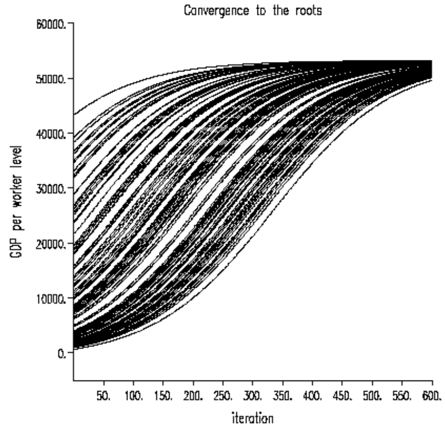

FIG 3 Convergence to the Upper Root

Thus we would argue that the very simple spatial econometric model has some dynamic implications that are not inconsistent with the FKV theory described earlier. For instance the functional form and estimated parameters indicate that the initially low wage economies will see quite sharply rising wages at some stage of their development, leading ultimately to a long-run stable equilibrium at which GDP per worker tends to equalise across countries. Figure 4 shows that wage level dispersion initially increases then falls to zero.

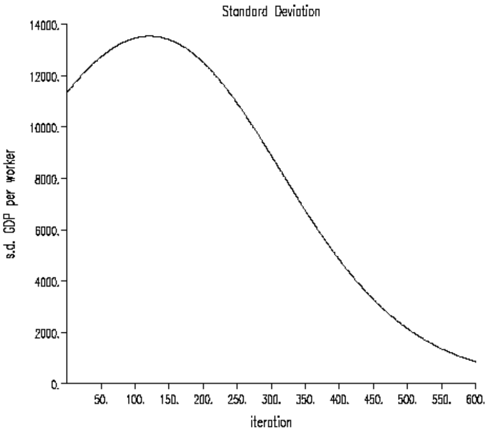

FIG 4 Standard Deviation in GDP per worker - Convergence to Upper Root

Some countries reach the equilibrium level earlier than others, with the poorest countries responding most slowly and only reaching the equilibrium wage level at some distant point in the future. This is suggestive of a globalisation process akin to FKV in which polarization increases but then diminishes.

DYNAMICS WITH LOWER ROOT UNCERTAINTY

But examining the results in more detail, we now explore the implications of alternative parameter values and take account of the uncertainty about the true value of the parameters, as measured by the regression coefficient standard errors. Acknowledging that *a*, *b* and *c* are random variables implies that the roots *x* are also random variables, the problem now is to measure the uncertainty associated with *x*, particularly the lower root, since whether or not a country falls lies above the lower root determines whether or not it ultimately converges to the upper root. We obtain evidence about the distribution and moments of *x* using simulation methods. Defining *M* as the vector of expectations and Σ as the variance-covariance matrix, we use the ML point estimates in Table 3 for $\hat{a}, \hat{b}$ and $\hat{c}$, and hence $\hat{M}$, and the ML estimation also gives $\hat{\Sigma}$. Since we assume a normal distribution for the likelihood, we assume that the true distribution of *a*, *b* and *c* is a multivariate normal distribution $N(M, \Sigma)$ and we use $\hat{M}$ and $\hat{\Sigma}$ to generate pseudo-random numbers $\tilde{a}, \tilde{b}, \tilde{c}$ and from these we calculate $\tilde{x}_L$ and $\tilde{x}_U$. The method involves initially generating univariate normal random numbers, using the Box-Muller method (Box and Muller 1958), followed by a linear transformation involving *A* where *A* is calculated by a Choleski decomposition (which requires a positive semi-definite variance-covariance matrix); $AA' = \Sigma$, as described by Johnson (1987) and Tong (1990). This process is repeated 1000 times, giving 1000 realizations of $\tilde{a}, \tilde{b}, \tilde{c}$ and $\tilde{x}$. Figure 5 illustrates the range of outcomes, giving the quadratic functions based on the ML estimates (as in Figure 2) and on the $\tilde{a}, \tilde{b}, \tilde{c}$ consistent with 5^{th} (-11356) and 95^{th} (2481) sample percentiles from the $\tilde{x}_L$ distribution.

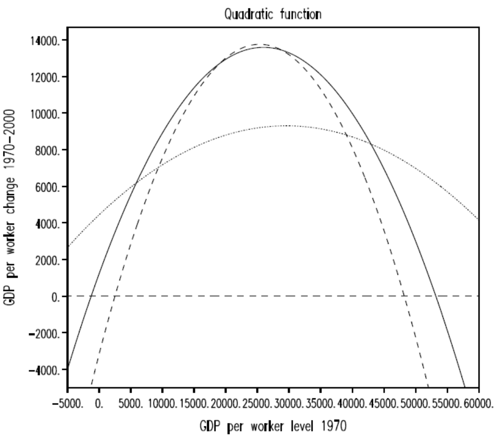

FIG 5 Quadratics for the ML estimates and 5^{th} and 95^{th} sample percentiles

The implications for convergence are as follows. Assume that the lower root $\tilde{x}_{L,0.95}$ takes a value equal to 2481, which is the 95^{th} sample percentile from the $\tilde{x}_L$ distribution. There are 16 countries with initial GDP per worker below this conjectured lower root, so we infer from this that there is a 0.05 probability that up to 16 countries do not converge. Table 4 gives various conjectured roots, probabilities and numbers of non-convergent countries.

Table 4

Probabilities of non-convergence

Lower root $\tilde{x}_L$	Probability	Number of countries
855	0.20	1
1870	0.10	11
2481	0.05	16

3162	0.025	24

From the simulation, we use the parameters $\tilde{a}, \tilde{b}, \tilde{c}$ that generated the lower root closest to $\tilde{x}_{L,0.95}$ = 2481. Figure 6 shows the 16 countries below the unstable lower root, converging to zero. Figure 7 similarly shows that rather than increasing polarization followed by convergence to zero dispersion, polarization is permanent.

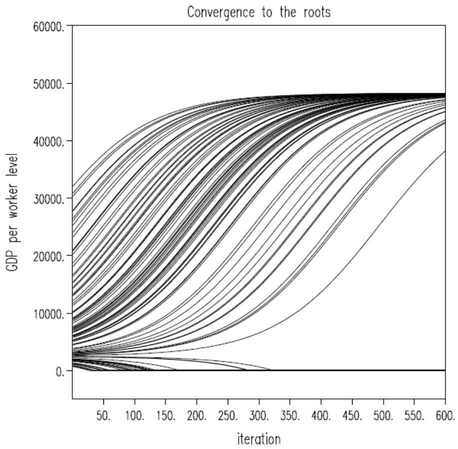

FIG 6 Convergence to Upper Root and zero

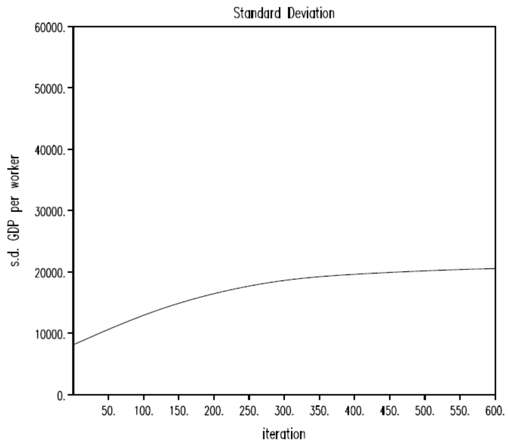

FIG 7 Evolution of Standard Deviation of the Wage Distribution

The 16 countries are, bar at least one, as one would expect. These are the poorest countries in 1970 (for which we have data[3]) comprising Benin, Burkina Faso, Burundi, Republic of Congo, Ethiopia, The Gambia, Guinea-Bissau, Kenya, Lesotho, Malawi, Mali, Nepal, Rwanda, Tanzania, Uganda plus China. The exceptional growth of China that has actually taken place highlights the assumption, which is this case at least is a false one, of no change in institutional and infrastructural conditions. Of course, in China and possibly elsewhere, institutions and infrastructure have changed radically, and the precise number of countries will depend on the set of realizations obtained leading to the sample percentiles.

[3] See the Appendix for the full list of 98 countries.

In an exploration of robustness, we repeat the analysis based on 1960 levels[4] and changes from 1960-2000. Using ML, the fit is slightly worse, with $\hat{\sigma}$ = 9496.96 and log likelihood equal to -1039.2504, but the estimated parameters are $\hat{c}$ = 1016.910, $\hat{b}$ = 1.908, $\hat{a}$ = -0.00004593 $\hat{\rho}$ = 0.085, with t- ratios equal to 0.33, 3.67, -2.81 and 9.38 respectively, and this supports the assumption of a significant quadratic function and spatial autoregressive error process. Following exactly the same procedure as described above, this leads to $\tilde{x}_{L,0.95}$ = 1598 with 11 countries below this lower root, comprising the above 16 minus Benin, Guinea-Bissau, Kenya, Mali and Rwanda. It is evident that the prediction of a small but not insignificant probability (0.05) of convergence to zero (subsistence) productivity and wages for a group of countries is also supported by our supplementary data.

Overall, these results show that convergence in wage levels as a long-run equilibrium for all countries is not supported by detailed analysis of the data. As Table 4 and the robustness analysis shows, international wage differentials may be both a short-term and a long-term phenomenon.

CONCLUSIONS

This paper has shown that spatial econometric analysis leads to conclusions that wage levels may evolve in a way that appears to be consistent with the FKV model discussed in this paper, with the existence of a non-monotonic relationship between wage change and wage level producing dynamics that are probably not dissimilar to what we might see under the FKV model with many industries and many countries. However, further analysis taking account of the uncertainty associated with the estimated roots that control the dynamics of the convergence process shows that there is a possibility that not all countries will converge, and given the acknowledged limitations of the FKV model, which omits many of the causes of non-convergence, this empirical result does point to a need to reformulate the model to try to take account of the existence of omitted factors. The quadratic relationship with uncertain roots implies that, depending on a country's initial position with respect to the roots, it will converge on a stable upper root or may in a small number of cases go into free fall, with no wage level low enough to attract capital and ignite a process of upward movement in wage levels. The presence of a significant quadratic relationship only becomes apparent after controlling for another spatial mechanism identifiable as part of the globalization process, namely the spillover of shock-effects between countries. These have important implications, as illustrated by an analysis of the impact of extraordinary shocks to leading economies in the parallel analysis in Fingleton (2007). It is hoped that, by highlighting the missing elements in the FKV model, this paper will cause future theory, building on FKV's seminal contributions, to move in the direction of greater realism.

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[4] For Tunisia we use 1961 because there are no data for 1960. There is no data pre-1970 for Hungary, so we calculate the deviation from the 1970 mean in units of standard deviation, and set the 1960 value equal to the same number of standard deviations from the 1960 mean.

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Appendix

Countries included in the analysis : Argentina, Australia, Austria, Bangladesh, Barbados, Belgium, Benin, Bolivia, Brazil, Burkina Faso, Burundi, Cameroon, Canada, Cape Verde, Chad, Chile, China, Colombia, Comoros, Republic of Congo, Costa Rica, Cote d`Ivoire, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Finland, France, Gabon, The Gambia, Ghana, Greece, Guatemala, Guinea, Guinea-Bissau, Honduras, Hong Kong, Hungary, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, republic of Korea, Lesotho, Luxembourg, Madagascar, Malawi, Malaysia, Malawi, Mali, Mauritius, Mexico, Morocco, Mozambique, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Pakistan, Panama, Paraguay, Peru, Philippines, Portugal, Romania, Rwanda, Senegal, Seychelles, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Syria, Tanzania, Thailand, Togo, Trinidad &Tobago, Tunisia, Turkey, Uganda, United Kingdom, United States, Uruguay, Venezuela, Zambia, Zimbabwe.