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DOES TRADE OPENNESS AFFECT THE SPEED OF OUTPUT CONVERGENCE? SOME EMPIRICAL EVIDENCE

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Abstract

In this paper we develop flexible techniques for measuring the speed of output convergence between countries when such convergence may be of an unknown non-linear form. We then calculate these convergence speeds for various countries, in terms of half-lives, using a time-series data-set for 88 countries. These calculations are based on both nonparametric kernel regression and 'fuzzy' regression, and the results are compared with more restrictive estimates based on the assumption of linear convergence. The calculated half-lives are regressed, again in various flexible ways, on cross-section data for the degree of openness to trade. We find evidence that favours the hypothesis that increased trade openness is associated with a faster rate of convergence in output between countries.

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1. Introduction

There is a long history of research, both theoretical and empirical, that provides at least a consensus affirmative answer to the question: 'Does openness to trade result in the growth of *per capita* income (say, GDP)?' When the question is refined to become: 'Is openness to trade associated with *convergence* in income (output) across countries?', the answer is far less clear. However, there is recent empirical evidence that supports a positive answer to this question too, and so in this paper we refine the question even further, and ask: 'Does openness to trade affect the *speed of convergence* in output across countries?' This question does not appear to have been the subject of systematic empirical analysis before.

In this paper we present empirical evidence that offers reasonable support for the hypothesis that there is a positive relationship between the speed of output convergence and trade openness. The latter is defined as a country's total trade (exports plus imports) as a fraction of GDP; and the speed of output convergence is measured in terms of the half-life for closing the 'gap' between a country's real *per capita* GDP and that of the 'leading' country in the group under consideration. We base our analysis on a set of data involving 88 countries at various levels of development. The 'leading country' is the U.S.A..

The convergence half-lives are constructed from the time-series data, allowing for both linear and nonlinear convergence. Following a recent suggestion in the purchasing power parity literature, they are based on estimates of the Lyapunov exponents of the output data. Linear and nonlinear cross-section regressions are then estimated to test if there is a significant *negative* relationship between convergence half-lives and trade openness. At both stages of the analysis we make extensive use of some new results relating to regression modeling based on fuzzy clustering, and we use quantile regression and other robust procedures to deal with outliers in the data.

In the next section we provide a brief discussion of the literature associated with the questions that were posed in the opening paragraph above. Section 3 provides the details of the estimation of the output convergence speeds, and links our analysis to the purchasing power parity literature. Fuzzy clustering and fuzzy regression methods are introduced in section 4; and the data that are used in our empirical analysis are described in section 5. Our main results relating to both output convergence half-lives, and the negative link between these and trade openness, appear in section 6; and section 7 concludes the paper with a summary and some comments regarding future research.

2. Output convergence and trade

Previous empirical testing of the income convergence hypothesis has been based on both cross-section and time-series data, with mixed results. Essentially, the cross-section results have supported convergence, while the earlier time-series results did not. For further details, see Baumol (1986), Dowrick and Nguyen (1989), Barro (1991), Mankiw *et al.* (1992), Bernard (1992), Quah (1993), Barro and Sala-i-Martin (1991, 1992, 1995), Bernard and Durlauf (1995, 1996), Cellini and Scorcu (2000), *inter alia*, and the excellent survey by Durlauf and Quah (1999). However, the more recent time-series evidence has been more favourable towards the convergence hypothesis. Greasley and Oxley (1997) find more convergence than do Bernard and Durlauf (1995) by taking account of structural breaks in the data; and using a Kalman filter approach St. Aubyn (1999) finds convergence, after World War 2, between the U.S.A. and every G-7 country except Canada. Nahar and Inder (2002) criticize the definition of convergence that is used by Bernard and Durlauf, and the alternative approach that they propose yields evidence of convergence between 16 out of 21 OECD countries, relative to the U.S.A.. The robustness of their results to changes in the sample period and the set of countries is demonstrated by Giles and Feng (2005).

The bulk of the empirical literature associated with the convergence hypothesis has been relatively narrow in its focus, concentrating only on certain moments or other features of the distribution of growth rates. The familiar notions of 'β-convergence' and 'σ-convergence' both fall into this category. Quah (1993, 1997) offers a more general viewpoint, and considers the full growth rate distribution. Recently, this position has been advanced and refined in several important directions by Maasoumi *et al*. (2005). Using both parametric and nonparametric methods, these authors consider the relationships between complete growth rate distributions, both across and within groups of countries, and they find evidence of 'clubs', rather than convergence. Their methodology allows for non-linearities in the evolutionary paths of the 'distance' between the growth rate distributions, where distance is measured in terms of entropy. This allowance for non-linearities is similar in spirit to the approach taken by Giles (2005). He uses fuzzy clustering to partition the growth rate data for different countries, and then measures convergence in terms of the distance between the centroids of the clusters. This also allows the distance to evolve along a non-monotonic path over time.

As the evidence regarding the convergence issue is undoubtedly mixed, and much hinges on the type of data and definition of convergence that is used, it may be desirable to re-phrase the second question posed in section 1 as: 'In those situations where there is evidence of *convergence* in *per capita* income (output) across countries, is this convergence associated with openness to trade?'. Standard international trade theory provides only a few strong results that point to a clear answer. It is clear that the flows of goods and services between countries will lead to the convergence of factor prices – at least under the rather strong assumptions of the factor price equalization theorem (Samuelson, 1948, 1949). However, as we discuss more fully below, convergence in factor prices need not imply convergence in output, and even if trade openness and output convergence co-exist, this does not necessarily imply that there is a *causal* relationship between the two. Neither does it mean that other variables are unimportant to the process of output convergence.

In the context of the economic growth literature, very little is said with regard to the role of international trade in the convergence process. In the traditional Solow-Swan model, convergence emerges in a closed-economy environment. In those endogenous growth models that allow for trade, the focus is on convergence to a steady-state rather than on convergence in the levels of output in different economies. These points have been made already by Slaughter (1997, 2001), Ben-David (1996), Ben-David and Loewy (1998), Ben-David and Kimhi (2000) and others.

Several of these authors, and others, have enhanced our understanding of this issue through various empirical studies. The results have been mixed, depending upon the definition of convergence that is adopted, the choice of statistical technique, the type of data, the time-period in question, and the level of development of the countries under consideration. The conclusions that emerge also depend at least partly on the distinction between studies that investigate trade *liberalization* and output convergence, and those that deal with the *degree of openness* to trade and convergence.

The few theoretical models and results that are available relate primarily to trade *liberalization*, which is not of explicit concern to us here. For example, Ben-David and Loewy (1998, 2000) develop models that predict that while trade liberalization will increase the steady-state output growths of all countries, those countries that participate directly in this liberalization most will benefit the most in terms of their relative income levels. Our own concern is with relationships between *per capita* output convergence and existing levels, or amounts, of trade (as reflected in the degree of openness of the economies in question). In this case, there are very few formal theoretical models to help us, and even fewer sharp results. Slaughter (1997) critiques three ways in which, it has been argued by various authors, trade may be associated with output convergence.

First, he points that the factor price equalization theorem relates to steady-state free-trade equilibria, whereas the notion of 'convergence' relates to movements *towards* a steady-state situation. Moreover, as he observes, even when factor prices are converging, if factor *endowments* are diverging sufficiently then *per capita* incomes can also diverge. Second, Slaughter notes that while trade can facilitate technology transfer between economies, and thus change the countries' factor prices, for this to result in changes in *per capita* output, we must avoid situations in which factor *endowments* are diverging sufficiently to offset the technology transfer effects. Finally, he observes that while it is possible for trade in capital goods to result in convergence in *per capita* outputs (by changing the countries' relative factor endowments), such convergence will not occur if factor *prices* are diverging too quickly. There seems to be no compelling theoretical reason that *per capita* income convergence and international trade *must* co-exist

As we have noted already, the associated empirical literature provides us with somewhat mixed evidence. Several of these recent empirical studies (*e.g.*, Ben-David 1993, 1994, Ben-David and Bohara, 1997), Ben-David and Kimhi (2000), and Slaughter (2001) focus on countries that have been involved in trade *liberalization* programs. The consensus of the results from all but the last of these studies is that there is a positive association between trade liberalization and *per capita* income convergence. In contrast, Slaughter (2001) finds that various post-1945 trade liberalizations appear to have led to income *divergence*, rather than convergence. On the other hand, Dollar (1992), Edwards (1993), Harrison (1996), Sachs and Warner (1995), Henrekson *et al.* (1997), Ben-David (1996), Giles (2005) and Stroomer and Giles (2003) all focus on the *level* of trade (or trade openness), rather than situations associated with trade liberalization programs, and their general conclusion is that there is a positive relationship between trade and *per capita* output convergence. In particular, Stroomer and Giles apply the time-series tests suggested by and Bernard and Durlauf (1995) and by Nahar and Inder (2002) for both bivariate and multivariate conditional convergence, and the multivariate results are especially supportive of the hypothesis that openness and convergence tend to co-exist.

On the negative side, O'Rourke (1996) concludes that migration was more important than trade for international convergence in the late nineteenth century; and Bernard and Jones (1996) conclude that freer trade results in income *divergence* across countries. In summary, while the jury is still out as to the role of trade openness in the output convergence process, much of the recent empirical evidence points to a positive association of some sort, and this suggests that more detailed investigations of these linkages would be interesting and useful.

3. Measuring the speed of convergence

Given that there is at least some evidence in support of income convergence between countries, and that trade openness may play a role in this, it is natural to turn to a modified version of the final question posed in our opening remarks in section 1. 'Does trade openness affect the *speed* of output convergence, in cases where the latter exists?'

In the international trade literature, a number of authors (*e.g.*, see Frankel, 1986, Diebold *et al*., 1991, Lothian and Taylor, 1996, and Rogoff, 1996) have measured the speed of convergence to purchasing power parity (PPP) by estimating the half-lives of deviations from PPP. We use this approach here to measure the speed of convergence in output by calculating half-lives of deviations from the output of the 'leading' country. In the PPP literature, the traditional way of obtaining such an estimate is to fit a simple AR(1) regression for the real exchange rate (q):

$$q_t = \rho q_{t-1} + \varepsilon_t \quad , \tag{1}$$

and then obtain the convergence half-life as

$$\tau = \ln(0.5) / \ln(|r|) \quad , \tag{2}$$

where 'r' is the Ordinary Least Squares (OLS) estimator of the slope parameter in (1), and the denominator in (2) measures the (absolute) speed of adjustment in the AR(1) process.[1]

Given the linearity of (1), the half-life in (2) is uniquely defined, independently of the initial value, q_0, and of the values of the deviations from PPP. While this assumed linearity is convenient, it is highly restrictive, and can lead to a bias in half-life estimates (Taylor, 2001). A number of recent studies (*e.g.*, Michael *et al*., 1997, Obstfeld and Taylor, 1997, O'Connell, 1998, Obstfeld and Rogoff, 2000, Taylor *et al*., 2001 and Shintani, 2002) have argued that one should use a smooth nonlinear AR(1) model:

$$q_t = f(q_{t-1}) + \varepsilon_t \quad , \tag{3}$$

where $f\,(q_{t-1})$ is a nonlinear conditional mean function.[2] In this case, defining a half-life measure is complicated by the fact that the nonlinear response function depends upon the initial value, q_0, and on the magnitudes and the signs of the shocks.

Recently, Shintani (2002) has explored the use of the largest Lyapunov exponent of the time-series for q_t as the basis for half-life measurement.[3] For the model (3), the Lyapunov exponent is defined as:

$$\lambda = \lim_{T\to\infty} T^{-1} \sum_{t=1}^{T} \ln |Df(q_{t-1})| \quad , \tag{4}$$

where $D\,f\,(q_{t-1})$ is the first derivative of the conditional mean function for (3). Shintani (2002) exploits the fact that as the Lyapunov exponent in a stable system with a steady state can be interpreted as an average speed of adjustment, a half-life measure analogous to that in (2) can be constructed as [4]

$$\tau^* = \ln(0.5) / \lambda \,. \tag{5}$$

Furthermore, Shintani then proposes that $D\,f\,(q_{t-1})$ can be estimated by fitting model (3) using nonparametric kernel regression, and obtaining the derivatives, $df\,(q_{t-1})$, of the fitted function.[5] Inserting these derivative estimates into (4) provides an estimator of (4), namely

$$l = T^{-1} \sum_{t=1}^{T} \ln |df(q_{t-1})| \quad , \tag{6}$$

for use in (5). Shintani notes that although the resulting estimator of (5) (say, t*) is not an *exact* half-life measure, it can be interpreted as the average of the half-lives of the locally linearized nonlinear processes.

Obtaining meaningful estimates of $D\,f\,(q_{t-1})$ by nonparametric kernel regression is problematic if the sample size is limited. In such cases, the highly flexible fuzzy regression estimator discussed by Giles and Draeseke (2003) is an attractive alternative, as is amply demonstrated by those authors. As we explain in the next section, fuzzy regression is able to capture arbitrary nonlinearities in the model extremely well, and it provides weakly consistent parameter estimates.

In the present study we are concerned with estimating the relationship between the speed of output convergence and the level of trade openness. To facilitate this we need quantitative measures of the speed of convergence of output to that of a 'leading' country. To the best of our knowledge, the only similar such measures that have been obtained previously by using *time-series* data are those of St. Aubyn (1999) for the G-7 countries, relative to the U.S.A..[6] His measures are in terms of each country's annual percentage rate of convergence to its long-run steady-state. When these are converted to half-lives, his five statistically significant estimates correspond to values that range between 5.1 and 13 years.[7] Clearly, St. Aubyn's results provide insufficient data for an analysis of the type that we have in mind. Moreover, a point that has not been addressed in the literature to date is that if output convergence takes place, then it may follow a nonlinear process. This suggests that Shintani's half-life measure, based on the Lyapunov exponent, may be a useful way of quantifying convergence rates in this context.

In the analysis that follows we use the derivatives of estimated fuzzy regression models to construct half-life estimates, t^*, for output convergence. Using the fuzzy regression approach to estimate the conditional derivative functions has the advantage of enabling us to deal with outliers in the data in a very simple, non-subjective, and effective manner. Various robust estimators are also considered in the context of the fuzzy analysis, and we also use nonparametric kernel regression by way of a comparison. We also experimented with the robust nonparametric estimator proposed by Yu and Jones (1998), but were unable to obtain sensible results with our data. This may reflect the modest sample size involved.

4. Fuzzy regression analysis

The following discussion is taken directly from Giles and Draeseke (2003), Stroomer and Giles (2003), and Giles and Mosk (2003). Fuzzy sets were first introduced by (Zadeh, 1965, 1987). The fuzzy c-means (FCM) algorithm (Ruspini, 1970, Bezdek, 1973, 1981; Dunn, 1974, 1977;) partitions the 'n' data-points into 'c' fuzzy clusters (where $c < n$), and simultaneously identifies the centers of these clusters. Let $\boldsymbol{x}_k$ be the k^{th} (possibly vector) data-point (k = 1, 2, ..., n); let $\mathbf{v}_i$ be the center of the i^{th} (fuzzy) cluster (i = 1, 2, ..., c); let $d_{ik} = \| \boldsymbol{x}_k - \boldsymbol{v}_i \|$ be the distance between $\boldsymbol{x}_k$ and $\boldsymbol{v}_i$; and let u_{ik} be the 'degree of membership' of data-point 'k' in cluster 'i', where :

$$\sum_{i=1}^{c}(u_{ik}) = 1.$$

We partition the data into the 'c' clusters, locate the cluster centers, and determine the associated 'degrees of membership', so as to minimize the functional

$$J(U,v) = \sum_{i=1}^{c}\sum_{k=1}^{n} (u_{ik})^m (d_{ik})^2 .$$

Values are assigned in advance for 'm' (> 1), and 'c'. The latter choice is constrained in part by the sample size, and after some experimentation we have used c = 3. We have set m = 2, which is a common choice. The FCM algorithm involves the following steps:

1. Select the initial locations of the cluster centers.
2. Generate a (new) partition of the data by assigning each data-point to its closest cluster center, based on the membership values.
3. Calculate new cluster centers from the revised partition of the data.
4. If the cluster partition is stable then stop. Otherwise go to step 2 above.

The Lagrange multiplier technique generates the following expression for the membership values to be used at step 2 above:

$$u_{ik} = 1 / \left\{\sum_{j=1}^{c}[(d_{ik})^2 / (d_{jk})^2]^{1/(m-1)}\right\} .$$

The cluster centers are updated at step 3 above *via* the expression

$$v_i = [\sum_{k=1}^{n} (u_{ik})^m x_k] / [\sum_{k=1}^{n} (u_{ik})^m] \ ; \quad i = 1, 2, ..., c.$$

The fixed-point nature of this problem ensures the existence of a solution in a finite number of steps. When the centers of the fuzzy clusters have been determined, each of the n data-points can be allocated to the cluster whose center it is closest to.

To illustrate fuzzy regression, consider the case where there is a single regressor (other than, perhaps, a constant intercept).[8] The fuzzy relationship to be estimated is:

$$y = f(x) + \varepsilon \quad ,$$

where the form of the functional relationship is unspecified (but will typically involve unknown parameters), and ε is a random disturbance term. No distributional assumptions need to be made about the latter. If the disturbance has a zero mean, the fuzzy function represents the conditional mean of the dependent variable, y. To this extent, the framework is the same as that which is adopted in non-parametric kernel regression.

The identification and estimation of the fuzzy model proceeds according to the following additional steps, once the fuzzy clusters have been established using the FCM algorithm:

5. Using the data for each fuzzy cluster separately, fit the models:

$$y_{ij} = f_i(x_{ij}) + \varepsilon_{ij} \quad ; \; j = 1,\ldots.,n_i \; ; \; i = 1,\ldots.,c$$

In particular, if the chosen estimation procedure is parametric least squares, then

$$y_{ij} = \beta_{i0} + \beta_{i1} x_{ij} + \varepsilon_{ij} \quad ; \; j = 1,\ldots.,n_i \; ; \; i = 1,\ldots.,c$$

6. Recalling that

$$\sum_{i=1}^{c} (u_{ik}) = 1 \quad ,$$

model and predict the conditional mean of y using:

$$\hat{y}_k = [\; \sum_{i=1}^{c} \; (b_{i0} + b_{i1} x_k) u_{ik} \;] \quad ; \; k = 1,\ldots.,n$$

where u_{ik} is the degree of membership of the k^{th} value of x in the i'th fuzzy cluster, and b_{im} is the least squares estimator of β_{im} (m = 0, 1) obtained using the i^{th} fuzzy partition of the sample.

7. Construct the derivative of the conditional mean with respect to the input variable:

$$(\partial \hat{y}_k / \partial x_k) = \sum_{i=1}^{c} \; (b_{i1} u_{ik}) \quad ; \; k = 1,\ldots.,n$$

The fuzzy predictor of the conditional mean of y is a weighted average of the linear predictors based on the fuzzy partitioning of the explanatory data, with the weights (membership values) varying continuously through the sample. This latter feature enables non-linearities to be modeled effectively. In addition, it can be seen that the separate modeling over each fuzzy cluster involves the use of fuzzy logic of the form "IF the input data are likely to lie in this region, THEN this is likely to be the predictor of the output variable", *etc*.. The derivative of the fuzzy conditional mean has the same potential for non-linearity. Under some very mild conditions, for a fixed choice of 'c' the fuzzy regression estimator is weakly consistent, and its rate of convergence is the same as that for the least squares estimator, namely $T^{1/2}$.

5. Data issues

Our data-set is that used by Stroomer and Giles (2003). It comprises *per capita* GDP data in real (1985) international prices, adjusted for terms of trade (RGDPTT), and trade openness data (OPEN) for 88 countries, over the period 1965 to 1990. The names of the countries in the sample are given in Tables 1 below. In keeping with other authors we have not included those oil-producing countries with extremely high *per capita* incomes in our sample. The real GDP time-series data are used to construct output convergence half-lives for each country with respect to the 'leading' country, the U.S.A., using $q_t = log(GDP_{i,t} / GDP_{USA,t})$, for country '$i$', in equations (1) or (3).[9]

We have taken the trade openness data (OPEN) for each of the countries in our sample from the *Penn World Table*, where openness is defined as the ratio of total nominal trade (*i.e.*, exports plus imports) to nominal GDP. The countries in our sample have trade openness values that span a very wide range, and Stroomer and Giles divided the countries into three groups, according to their degree of openness, by using the fuzzy c-means clustering algorithm. This resulted in a low-openness cluster of 50 countries; a medium-openness cluster of 21 countries; and a high-openness cluster of 17 countries. The results presented in the next section are based on output convergence half-lives that are estimated from the GDP data for each of the 87 countries (relative to the overall 'leader', the U.S.A.). We also conducted the same analysis, separately, for each of the openness clusters constructed by Stroomer and Giles, considering convergence to each cluster leader.[10] However, we were unable to obtain sensible results in this case, apparently due to the lack of dispersion in the relatively small samples. In addition, we repeated the analysis by taking the average of trade openness over the period 1965-1969 for each country, and once again the results given in the next section are robust to this choice of definition.

Before discussing our results, a final consideration is the stationarity of the time-series data used to estimate the convergence half-lives. As would be expected, the GDP data themselves possess unit roots, but of concern here would be unit roots in the various $q_t = log(GDP_{i,t} / GDP_{USA,t})$ series. We have tested the trend-stationarity of these data, against the I(1) alternative, using the well-known KPSS test (Kwiatowski *et al*., 1992). Critical values are supplied by KPSS and by Hornock and Larsson (2000).

6. Empirical results

The results of the tests for data stationarity appear in Table 1, and these clearly support the stationarity hypothesis, which has important implications for the quality of the half-life estimates that follow. As an aside, it should also be noted that these stationarity tests amount to applying the Bernard and Dulauf (1995) test for convergence in output. Our findings in Table 1 accord with the bivariate results of Greasley and Oxley (1997), who find evidence of bilateral convergence for a range of countries when they apply Perron's variant of the Dickey-Fuller test to allow for structural breaks in the data over their relatively long sample period.[11] So, one conclusion that can be drawn from this is that there is very strong evidence of bilateral output convergence (to the leading country) for the various countries in our data-set. Indeed, this evidence is somewhat stronger than that reported by Stroomer and Giles (2003) on the basis of augmented Dickey-Fuller tests.

Next, we have constructed output convergence half-lives using Shintani's (2002) approach, as outlined in section 3. Estimates of the derivatives needed to calculate the half-life values have been obtained by six different methods. These are: (i) OLS estimation of the linear AR(1) model (1), and the application of equation (2) above; (ii) as for (i), but with robust 'five quantile' (5Q) estimation replacing OLS to allow for outliers in the data; (iii) fuzzy regression estimation of the nonlinear AR(1) model (3), using three fuzzy clusters and with OLS applied at step 5 of the discussion in section 4 above, and the half-lives calculated from the Lyapunov exponent using equations (4), (5) and (6); (iv) as for (iii), but with '5Q' estimation in place of OLS; (v) as for (iii), but with nonparametric kernel regression used instead of fuzzy regression; and (vi) the threshold autoregressive (TAR) framework proposed by Caner and Hansen.[12]

Our calculations of the output convergence half-lives are summarized in Table 2. That summary is based on those half-life estimates that are positive, and the fact that some negative half-life estimates were obtained warrants comment. Clearly, such values are incompatible with the convergence hypothesis. Thus, it makes no sense to use them when testing the relationship between trade openness and convergence speed, particular given the conditional nature of the re-phrased hypotheses discussed in sections 2 and 3. One possible interpretation of these negative values is that they reflect *divergence* between the country in question and the leader, or movements towards different steady state positions. Another possibility is that the steady state may have been reached already, or over-shot. An examination of the negative half-life cases reveals that many of them relate to less developed economies, so convergence to a steady state that differs from that for the U.S.A. may be a reasonable conclusion.

While these half-life values are not of primary concern to us in their own right, they represent the data for the dependent variable in the models that we use to examine the relationship between convergence and trade openness. Accordingly, it is important to consider their characteristics and also to compare them with other evidence on output convergence rates. The following comments are based on the positive half-life estimates. As was noted in section 3, St. Aubyn (1999) provides limited such evidence based on time-series data for G-7 countries, suggesting half-lives of between 5.1 and 13 years. The median values reported in Table 2 are fully consistent with this, except when the TAR estimator or nonparametric kernel regression (case (v) above) are used.[13] In the latter case, half-lives of the order of one year arise for every country. This is a questionable result that may be due in part to the relatively small sample sizes (87 observations) that are being used.[14]

Accordingly, we have fitted regression models, either of the simple linear parametric form:

$$h_i = \alpha + \beta o_i + \varepsilon_i \quad ; \; i = 1, \ldots, N_+ \quad ; \tag{7}$$

or of the more general nonlinear form:

$$h_i = f(o_i) + \varepsilon_i \quad ; \; i = 1, \ldots, N_+ \quad ; \tag{8}$$

where h_i is the (positive) half-life for country i, and o_i is its openness to trade.

Evidence from cross-section studies by Barro and Sala-i-Martin (1991, 1992) and Mankiw *et al.* (1992) and Sal-i-Martin (1996) suggests convergence speeds of about 2% p.a. (*i.e.*, a half-life of h

= 34.3 years), but the credibility of these results based on cross-section data has been questioned by Bernard and Durlauf (1995) and others. For example, Evans (1997a) notes that OLS is unlikely to be consistent and instead develops a particular 2SLS estimator. His results for a cross-section of 85 countries imply a convergence rate of 8% to 9% p.a. (h = 7.3 to 8.3 years). Using panel data for the OECD countries (1960 -1985), Islam (1995) estimated the convergence speed to be 9.13% p.a. (h = 7.2 years). Evans (1997b) also uses panel data - both international and U.S. state-level - and he finds convergence rates of 6% p.a. (h = 11.2 years) and 16% p.a. (h = 4) respectively. Finally, Higgins *et al*. (2003) use a sample for over 3,000 U.S. counties, and report convergence rates of 6% to 8% p.a. (h = 8.3 to 11.2 years) from 2SLS regressions, and 2% p.a. (h = 34.3 years) when Evans' OLS estimator is used. This additional evidence also points strongly to the credibility of most of our own half-life estimates, and suggests that these data can be used with some confidence in our subsequent regression analysis.

If increased trade openness is conducive to faster income convergence, we would expect a negative relationship between h_i and o_i. All six methods of constructing the half-lives discussed above have been considered. The regressions themselves have been estimated in various ways. In the case of the parametric model (7) we have used OLS (with White's, 1980, correction to the standard errors to compensate for possible heteroskedasticity). Recent studies by Frankel and Romer (1999), Rodríguez and Rodrik (2001), and others have questioned the exogeneity of the openness variable and have suggested the use of instrumental variables (IV) estimation. We have also applied IV estimation to (7), using the ranking of the cross-section openness observations as an instrument (as proposed by Wald, 1940, Durbin, 1954, and others). In addition, we have applied Hausman's (1978) specification test to test if the openness regressor is independent of the error term in (7). Finally, we have also applied four robust estimators, all of which are linear functions of the regression quantiles (Koenker and Bassett, 1978), to guard against data outliers: the five quantile (5Q) estimator noted above; Tukey's (1977) 'trimean' estimator; the Gastwirth (1966) estimator, and the Least Absolute Errors (LAE) estimator. All of these estimators were implemented with the SHAZAM (2001) econometrics package. In the case of model (8) we have used nonparametric kernel regression and our own fuzzy regression estimator. The latter was applied in three different ways – with OLS estimation used with models of the form (7) over each of the three clusters; with IV estimation used with these three clusters; and with the 5Q estimator used with these three cluster models.[15]

The associated results are summarized in Table 3, with a and b denoting the estimates of the intercept and slope parameters respectively when the simple parametric model, (7), is used. We are interested primarily in the sign and the significance of the derivative of h_i with respect to o_i . In the case of model (8), these derivatives vary, observation by observation. Accordingly, we report just the (within-sample) median and mean slopes, when estimating this nonlinear model.[16] Finally, for the fuzzy regressions we also report the results of testing the hypothesis that the slopes of the (linear) within-cluster regressions are equal. With three clusters, the associated Wald test statistic is asymptotically Chi Square with two degrees of freedom, under the null. The associated p-values are given in Table 3, and in most cases we see that the null would be rejected at the 10% significance level (and often at a much lower level of significance). This provides strong support for estimating separate sub-models over each of the fuzzy clusters, and then combining the results using the membership functions, rather than fitting a single model (by OLS or by robust regression) over the full sample. The p-values associated with the Hausman test in both tables generally indicate that the hypothesis of an exogenous regressor cannot be rejected. There are two exceptions to this in Table 3 (at the 10% significance level). So, although IV estimation results are reported for completeness, for the most part these are superfluous – the OLS estimator is generally consistent. In addition, the Hausman test results provide mild evidence of causality from openness to output convergence, but not *vice versa*.

As was discussed in section 5, Stroomer and Giles (2003) undertook their analysis after using fuzzy clustering to divide the countries into three groups, according to their degree of openness. In our modeling here we examined the role of 'openness cluster' dummy variables in model (7), but found them to be totally insignificant. Accordingly, all of our results are based on the full sample of countries, and the sample size is N_+, in the terminology of Table 3. These results are generally supportive of the hypothesis that increased openness in trade promotes a faster rate (shorter half-life) of convergence of output between countries. The only consistent exceptions to this are when the TAR or robust 5Q estimators are used with the linear AR(1) model, (2), to estimate the convergence half-lives. The results based on the nonlinear model, (8), suggest an overall negative relationship between half-life and openness, though in general these mean and median values lack significance.[17]

6. Conclusions

In this paper we have undertaken an empirical investigation of one interesting aspect of the relationship between trade openness and economic growth, by considering output *convergence* and openness, and in particular by considering the *speed* of output convergence. To measure this speed we have drawn on concepts from the purchasing power parity literature. We have exploited the recent suggestions of Shintani (2002) that one should allow for nonlinear convergence, and measure the half-life of PPP convergence in terms of the Lyapunov exponent of the data. This has proven to be an important issue in relation to our output convergence measures. Using this approach we are able to calculate output convergence speeds, country by country, from time-series data. Such information has not been available on the basis of time-series data previously. Another novel feature of this paper is the application of recent developments in fuzzy clustering and fuzzy regression (*e.g.*, Giles and Draeseke, 2003; Giles and Mosk, 2003), not only to deal with the above-mentioned nonlinearities, but also to allow for very flexible functional forms when modeling the relationship between output convergence speed and trade openness. This flexibility appears to be important in such models, and our results include formal statistical support for this.

Our main results relate to regressions that 'explain' output convergence half-lives in terms of the degree of trade openness. We are not aware of other results of this type in the literature. Overall, the results from the set of data that we have considered suggest that there is reasonable evidence in support of the hypothesis that increased openness in trade is associated with a short half-life (high speed) of convergence in output across countries. The fact that we are using cross-section data for these regressions, rather than time-series data, precludes any formal testing for the presence and direction(s) of Granger *causality* between convergence and openness.

There are several directions in which this research can be extended. Clearly, additional sets of data need to be considered before strong conclusions can be drawn. The robustness of our results to the specification of the half-life/openness regressions, especially in terms of controlling for other factors, needs further examination. The fuzzy clustering and estimation procedures that we have introduced and used in this paper are readily applied to multiple regression problems, as Giles and Draeseke (2003) have demonstrated. This promises to be a fruitful basis for a more detailed empirical analysis of the relationship between the speed of output convergence and the degree of trade openness. Finally, we concur with Maasoumi *et al.* (2005) that more attention needs to be given to measures of well-being beyond simply *per capita* income. Recent efforts by Giles and Feng (2005) provide some initial results that are based on some of the empirical techniques adopted in this paper, but much remains to be done in this regard. In particular, the role of international trade in the convergence of more general quality-of-life measures is the focus of current research by the authors.

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Table 1a. Unit root tests – low openness countries*

Country	KPSS (Trend-stationary)	Country	KPSS (Trend-stationary)
Argentina	0.128$	Mali	0.089
Australia	0.126$	Mexico	0.105
Bangladesh	0.083	Morocco	0.087
Brazil	0.118	Myanmar	0.088
Burkin Faso	0.087	Nepal	0.089
Burundi	0.089	Niger	0.088
Cameroon	0.090	Pakistan	0.085
Canada	0.095	Paraguay	0.093
Chile	0.085	Peru	0.112
China	0.087	Philippines	0.095
Colombia	0.094	Poland	0.114
Dominican Rep.	0.100	Romania	0.090
Ecuador	0.097	Rwanda	0.090
Ethiopia	0.089	Spain	0.121$
France	0.124$	Sudan	0.090
Germany (W.)	0.090	Syria	0.105
Ghana	0.090	Thailand	0.087
Greece	0.118	Turkey	0.099
Guatemala	0.103	U. K.	0.091
Guinea-Biss	0.093	U.S.S.R.	0.094
Haiti	0.091	Uganda	0.090
India	0.086	Uraguay	0.096
Italy	0.085	Yugoslavia	0.114
Japan	0.092	Zaire	0.090
Madagascar	0.089		

* The series being tested are $q_t = log(GDP_{i,t} / GDP_{USA,t})$.

$ Reject trend-stationary at 10% significance level, but not at the 5% significance level.

(*In all other cases* we cannot reject trend-stationary at the 10% significance level.)

Table 1b. Unit root tests – medium openness countries*

Country	KPSS (Trend-stationary)	Country	KPSS (Trend-stationary)
Angola	0.081	Nicaragua	0.104
Austria	0.088	Panama	0.108
Central African Rep.	0.104	Papua New Guinea	0.109
Costa Rica	0.090	Portugal	0.096
Denmark	0.105	Senegal	0.093
Honduras	0.083	Sri Lanka	0.088
Hungary	0.092	Switzerland	0.097
Iceland	0.097	Taiwan	0.086
Israel	0.096	Trinidad & Tobago	0.128[$]
Ivory Coast	0.169[#]	Tunisia	0.110
Korea (S.)	0.107		

* The series being tested are $q_t = log(GDP_{i,t} / GDP_{USA,t})$.

$ Reject trend-stationary at 10% significance level, but not at the 5% significance level.

\# Reject trend-stationary at 5% significance level, but not at the 2.5% significance level.

(*In all other cases* we cannot reject trend-stationary at the 10% significance level.)

Table 1c. Unit root tests – high openness countries*

Country	KPSS (Trend-stationary)	Country	KPSS (Trend-stationary)
Barbados	0.080	Lesotho	0.079
Belgium	0.117	Luxembourg	0.103
Botswana	0.121[$]	Malta	0.094
Cape Verde Is.	0.090	Puerto Rico	0.080
Djibouti	0.086	Seychelles	0.086
Gabon	0.086	Singapore	0.080
Guyana	0.134[$]	Suriname	0.086
Hong Kong	0.117	Swaziland	0.087
Ireland	0.110		

* The series being tested are $q_t = log(GDP_{i,t} / GDP_{USA,t})$.

$ Reject trend-stationary at 10% significance level, but not at the 5% significance level.

(*In all other cases* we cannot reject trend-stationary at the 10% significance level.)

Table 2. Half-life estimates*

	Method for Constructing Half-Lives					
	OLS	5Q	Fuzzy Regression OLS	Fuzzy Regression 5Q	Kernel	TAR
N_+	37	27	66	53	87	81
Mean	76.4	9.1	6.7	16.6	1.4	1.0
Median	4.1	3.2	4.7	5.2	1.5	0.5

* ‘5Q’ denotes robust regression using the ‘five quantile’ method in the SHAZAM (2001) package.
N_+ is the number of positive estimated half-lives.

Table 3. Speed of convergence regressions*

	Method for Constructing Half-Lives											
	OLS		5Q		Fuzzy Regression OLS		Fuzzy Regression 5Q		Kernel		TAR	
Estimator	a	b	a	b	a	b	a	b	a	b	a	b
OLS	134.290	-1.032	8.230	0.013	9.091	-0.045	18.733	-0.038	1.478	-0.001	0.753	0.004
	(2.49)	(-1.83)	(2.11)	(0.40)	(5.45)	(-2.41)	(2.57)	(-0.39)	(23.81)	(-0.78)	(4.01)	(1.08)
5Q	31.627	-0.110	3.910	0.025	6.135	-0.019	10.435	-0.037	1.511	-0.001	0.546	0.002
	(32.04)	(-8.05)	(4.62)	(2.45)	(13.97)	(-2.67)	(8.88)	(-2.09)	(135.00)	(-7.78)	(22.63)	(5.77)
Gastwirth	17.212	-0.115	1.344	0.040	5.529	-0.017	8.666	-0.039	1.569	-0.002	0.518	0.001
	(3.19)	(-1.55)	(1.25)	(3.03)	(8.30)	(-1.58)	(5.75)	(-1.72)	(45.9)	(-3.79)	(11.13)	(1.38)
Tukey	15.168	-0.048	3.030	0.030	5.826	-0.016	9.210	-0.039	1.529	-0.002	0.551	0.001
	(1.84)	(-0.42)	(2.84)	(2.33)	(8.75)	(-1.52)	(3.20)	(-0.91)	(45.8)	(-3.10)	(7.68)	(0.66)
LAE	5.844	-0.022	1.234	0.042	5.296	-0.012	8.508	-0.037	1.555	-0.002	0.488	0.001
	(5.45)	(-1.48)	(2.65)	(7.34)	(5.83)	(-0.85)	(3.70)	(-1.08)	(23.9)	(-1.66)	(10.69)	(1.84)
IV	175.55	-1.769	7.635	0.022	9.825	-0.060	17.826	-0.022	1.526	-0.002	0.601	0.007
	(3.41)	(-2.32)	(1.40)	(0.32)	(6.07)	(-2.26)	(2.01)	(-0.16)	(19.42)	(-1.36)	(2.38)	(1.79)
	{2.83;	0.09}	{0.05;	0.81}	{1.86;	0.17}	{0.13;	0.72}	{1.87;	0.17}	{1.74	0.19}
	Mean Slope	Median Slope	Mean Slope	Median Slope	Mean Slope	Median Slope	Mean Slope	Median Slope	Mean Slope	Median Slope	Mean Slope	Median Slope
FuzzyOLS	-2.663	-3.342	0.135	0.158	-0.015	-0.053	0.164	-0.125	-0.005	-0.006	0.005	-0.011
	(-0.25)	(-2.70)	(0.11)	(1.84)	(-0.05)	(-0.29)	(0.13)	(-0.01)	(-0.27)	(-0.80)	(0.16)	(-3.00)
	[0.60]		[0.20]		[0.00]		[0.00]		[0.00]		[0.00]	
FuzzyIV	-2.842	-3.555	0.110	0.134	-0.019	-0.075	0.131	-0.166	-0.005	-0.007	0.006	-0.012
	(-0.26)	(-2.87)	(0.09)	(1.55)	(-0.06)	(-0.41)	(0.11)	(-0.13)	(-0.30)	(-0.92)	(0.19)	(-3.27)
Fuzzy5Q	-0.541	-0.677	0.061	0.064	-0.050	-0.108	0.200	0.019	-0.004	-0.006	0.003	-0.003
	(-0.05)	(-0.55)	(0.05)	(0.74)	(-0.16)	(-0.59)	(0.16)	(0.01)	(-0.24)	(-0.76)	(0.10)	(-0.75)
Nonparametric	-1.377	-1.660	0.008	0.014	-0.048	-0.054	-0.027	-0.101	-0.001	-0.002	-0.053	-0.053

* t-values appear in parentheses. In the case of OLS these are based on White's (1980) heteroskedasticity-consistent standard errors.

Hausman exogeneity test statistics and the associated p-values appear in braces below the IV t-values.

p-values for the Wald test, for the joint hypothesis that the slopes in each of the OLS sub-regressions for the separate fuzzy clusters are equal, appear in square brackets.

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Footnotes

1. In practice, an intercept may is usually included in equation (1). Taking the absolute value of the slope estimate allows for the possibility of oscillatory behaviour.
2. As in (1), we are assuming that the error has a zero mean. In the PPP studies, TAR or STAR models have generally been used to capture nonlinearities in (3). See also Paya *et al*. (2003).
3. See also Potter (2000), footnote 10.
4. If the system is linear, the expression in (5) collapses to that in (2).
5. Specifically, he uses the local polynomial variant of nonparametric kernel regression, as suggested by Fan and Gijbels (1996).
6. The remaining six countries are Canada (0.4% p.a.), France (12.7% p.a.), Germany (7.7% p.a.), Italy (5.2% p.a.), Japan (0.5% p.a.) and the U.K. (6.9% p.a.). The estimated (constant) convergence speeds are to each country's individual steady-state, based on a sample period of 1890-1989. (The estimates for Canada and for Japan are not statistically significant.) Convergence speeds that emerge from studies based on cross-section and panel data are discussed in section 6.
7. If the (constant) convergence rate is r% p.a., the half-life is $h = \{ln\ (0.5) / ln\ [1-(r / 100)]\}$ years.
8. This is the case that applies in the present study. The following analysis generalizes easily when there are multiple regressors, though some additional concepts from fuzzy set theory (*e.g*., the counterparts to the usual intersection and union operators) are needed in this case. Giles and Draeseke (2003) provide full details of this, and several modeling applications. Also, see Giles (2005) and Giles and Feng (2005).
9. Convergence implies $(GDP_i\ /\ GDP_{USA}) = 1$, just as for PPP. This in turn implies a zero conditional mean when we take logarithms.
10. These leaders are the U.S.A., Switzerland and Luxembourg for the low, medium and high openness clusters respectively.
11. See Perron (1989). We do not have any significant structural breaks in our time-series.
12. See footnote 15 below for further discussion regarding the choice of the number of fuzzy clusters. GAUSS code for implementing the TAR estimator was obtained from Bruce Hansen's webpage, **http://www.ssc.wisc.edu/~bhansen/**. We are grateful to one of the referees for suggesting the use of this estimator.
13. The large mean value for the half-lives based on method (i) is due to one or two extreme values. This underscores the usefulness of using a robust regression estimator.

14. Shintani (2002) uses samples with approximately 100 observations, and his estimated half-lives (for adjustment to PPP) based on nonparametric estimation are generally somewhat smaller than those based on OLS estimation of a linear AR(1) model.
15. The NONPAR routine in SHAZAM was used for the kernel regression with the second data-set, and our own code (written in the SHAZAM command language) was used for all of the fuzzy clustering and fuzzy regression analysis. The latter code is available on request to the authors. Although most of the fuzzy regression is based on three clusters, only two clusters were used when the half-lives were obtained by OLS or 5Q regression. This was because in these cases a third cluster resulted in insufficient degrees of freedom.
16. The 't-values' associated with these mean and median values are taken to be asymptotically standard normal.
17. We do not report 't-values' for the mean and median slopes in the case of nonparametric estimation, as it is not clear how these should be computed.