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Big Bang vs. Gradualism – A Productivity Analysis

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Abstract. In the beginning of the 1990s, the former socialist countries of Eastern Europe and the Soviet Union began reforming their economies. Yet despite two decades of research, it is still unclear which reform path – gradual or radical – is better for long-run growth. Unlike most other studies on the topic, which concentrate on the growth of output per capita, this paper compares the two alternative reform approaches based on the analysis of productivity.

We estimate a Malmquist multifactor productivity index for 22 transition economies over 17 years to compare their relative performance depending on their speed of reform. The Malmquist index is further decomposed into efficiency and technological change, and statistical inference is obtained using a smoothed bootstrap procedure.

The main results are that the radical reformers exhibit higher rates of productivity growth in the initial years of transition, while the gradual countries do better in the later years. Over the whole time period a gradual reform strategy is superior to faster reforms. These findings have important implications for reforms in the remaining non-market economies and many developing countries.

Keywords: Transition economies, Malmquist, speed of reforms, bootstrap.

1. Introduction

In the early 1990-ies nearly all socialist countries began transitioning to the free market system. Some countries opted for rapid reforms, whereas others chose a more moderate approach. Nearly two decades later we are taking in this paper another look on which reform strategy turned out to be superior. Lessons learned from this analysis still have important ramifications for future policy decisions, as not all countries have completed the transformation of their economies and a few have not even started the process of transition. Furthermore, many developing countries are faced with the need to reform their economies, and analyzing transition countries may provide valuable insights for their development.

Each of the two routes of transition has its advantages and disadvantages. The Big Bang strategy (or shock therapy) promises rapid improvements in living standards after a short period of painful economic contraction. Poland is frequently regarded as the best example of a successful shock therapy as a brief period of hyperinflation in the early 1990s, large budget deficits, and falling per capita income were succeeded by dramatic improvements. According to Sachs (1994, p. 275), “Poland achieved the earliest return to positive overall economic growth in the whole region, in 1992, leading all of Europe in economic growth in 1993…" But not all countries that implemented a Big Bang strategy experienced a similar pattern. Kyrgyzstan, for example, has experienced an extended economic crisis, making it one of the worst performing transition economies. After the start of transition, a staggering 72.5 percent of the country's population dropped below the poverty line of $4 per day (UNDP Human Development Report 2007/2008). The alternative to the Big Bang approach is Gradualism. Conventional wisdom maintains that introducing reforms gradually inflicts less short-run socio-economic pain, but improvements in standards of living may not come about as fast as with a successful Big Bang reform.

A number of recent studies (such as IMF, 2000; Mitra and Selowsky, 2002; Fischer and Sahay, 2000; and Popov, 2000 and 2007) have investigated the effect of the pace of reforms in the context of transition economies. However, these and related papers focus for the most part on the impact of the speed of transition on growth rates of output. Output growth can be due to either factor accumulation or improvements in productivity, which is a more sustainable long-run source of growth (Van den Berg, 2001). Thus, in this paper we are interested in using a productivity index to evaluate how the speed of reforms affects productivity growth.

To our knowledge only two papers (Deliktaş and Balcilar, 2005, and Kök and Deliktaş, 2004) have investigated a related issue using similar methods. Deliktaş and Balcilar (2005), look at various determinants of growth and productivity performance, but do not provide an in-depth analysis of Big Bang versus Gradualism. Kök and Deliktaş (2004) focus on the efficiency convergence among transition economies during 1991-2002, but not on the effects of the speed of reforms.

The rest of the paper begins with a brief literature review on alternative reform strategies, followed by two sections of methodology. The data is described in section five, and the results are discussed in section six. The final section contains concluding remarks.

2. Big Bang vs. Gradualism

The recent literature on economic reforms widely supports the view that institutions are a major determinant of growth (Blanchard and Kremer, 1997; Fischer et al., 1996; Sachs, 1996; De Melo and Gelb, 1996; Selowsky and Martin, 1997; Hall and Jones, 1999; Acemoglu et al., 2001; and Eicher and Schreiber, 2005; Grigorian and Martinez, 2001). In this paper we evaluate the effect of the speed of institutional changes, i.e. the speed of reforms, on factor productivity in the formerly socialist countries. More specifically, we compare the productivity impact of the Big Bang approach to the impact of Gradualism.

Wei (1997, p. 1236) and Williamson (1991), define Gradualism as a "sequential implementation of minimum bangs." A minimum bang is a simultaneous introduction of a minimum set of reforms, which can be implemented independently of other reforms. Big Bang, or shock therapy, on the other hand, is defined by Åslund et al. (1996) as a case in which a country tries to implement a maximum of reforms in a short period of time.

Mainstream research suggests that transition should encompass six major areas: macroeconomic stabilization, price liberalization, trade liberalization and current account convertibility, creation of a social safety net, and the development of the institutional and legal framework for a market economy (Lipton and Sachs, 1990a; Fischer and Gelb, 1991; and Sachs, 1996).[1] Policy recommendation papers have favored complete stabilization and fastest reforms. Results in formal models, on the other hand, support a more gradual approach as the cost of rapid transition is too high. Individual country studies take the middle ground by acknowledging the benefits of both reform strategies (Åslund et al., 1996).

[1] For more information about the optimal sequencing of reforms see Edwards (1990), McKinnon (1991), Fischer (1993), and Patterson (1996).

In the following, we provide a brief outline of the most frequently cited advantages and disadvantages of Big Bang and Gradualism.

A radical reform strategy, as argued by Roland and Verdier (1994), provides a critical scale of the private sector in the economy so that privatized firms can become more efficient. It also might increase the credibility of reforms (Lipton and Sachs, 1990a; 1990b) and reduce political resistance as it does not allow reform opponents to get organized (Krueger, 1993). Martinelli and Tommasi (1995) argue along the same lines as they conjecture that if a reform needs a consensual approval, sequential plans may not work, owing to time-inconsistency. Furthermore, in the context of price reforms, a gradual reform is undesirable because it may induce intertemporal speculation (Van Wijnbergen, 1992). Roland (1994) argues that the Big Bang strategy is preferable because it provides incentives for economic agents and reduces the size of the state sector more rapidly. Lastly, the World Bank (1991) states that more radical reforms simply bring about their benefits more quickly.

A more gradual approach, on the other hand, may avoid excessive costs, especially for the government budget (Dewatripont and Roland, 1992a; 1992b), and an excessive reduction in living standards at the beginning of reforms. Contrary to the shock therapy, Gradualism also allows trial-and-error and mid-course adjustment (The World Bank, 1991). Furthermore, the government can gain incremental credibility for the reforms when reforming at a slower pace. When outcomes of reforms are uncertain to individuals, a gradual or sequential approach splits the resistance force and can therefore increase the chances for survival of the program (Roland, 1994; Wei, 1997). Further, gradual privatization causes the best firms to enter the market first and thus leads to an automatic screening mechanism for financial markets and investors. This allows for the emergence of a sound financial system that permits further economic reforms without *ex-ante* or *ex-post* policy constraints (Roland, 1994). Lastly, economic agents use expected prices for their investment and production decisions. Privatization changes prices, induces uncertainty, and might lead to misallocation (Goodhue et al., 1998). The faster the privatization comes about, the more misallocation is likely to occur.

Previous research on the relationship between output decline and reforms is somewhat ambiguous. Whereas some theoretical models predict a substantial output decline in the presence of nominal rigidities and/or sector-specific capital (e.g. Mehlum, 2001),[2] Åslund et al. (1996) and Fischer (1993) do not observe any negative correlation between output change and various measures of reforms. Quite the contrary, given similar starting conditions, countries that followed more radical reforms fared better in terms of GDP growth, unemployment rates and institutional development than their gradualist counterparts (Åslund et al., 1996). The conventional expectation of the effect of institutional reforms is an initial dip in output followed by an increase in output after about one or two years (Fischer and Sahay, 2004). Structural reforms lead to a decline in output due to the restructuring of the large state sector. This initial decline is more severe as more reforms take place.[3] At the same time, however, reforms increase output in the private sector and lead to higher subsequent growth rates of output. The net effect is ambiguous in the short run,[4] but it can be expected that in the long run the gains will outweigh the costs. Results by De Melo et al. (1997) support this claim as they find that the speed of reforms has a negative impact on economic performance, whereas the accumulated stock of reforms has a positive impact. In line with these results are findings by Selowsky and Martin (1997) and a simulation study on the Chinese economy by Feltenstein and Nsouli (2003) that show that initially output does decline, but these welfare losses are rapidly compensated by higher subsequent growth rates.

[2] Goodhue et al. (1998) develop an alternative transition model that is based on learning. If privatization and liberalization are very rapid, uncertainty is predominant, which increases the cost of adapting to the market. In general, the Big Bang strategy is more beneficial the longer the time horizon of the government and the lower the learning costs.
[3] The initial output decline is vastly determined by the initial conditions (Berg et al., 1999).
[4] According to Berg et al. (1999), the net effect might be positive even in the short run.

Whereas most of the aforementioned studies focus on growth of output, the present paper analyzes the impact of reforms on total factor productivity. There is a consensus in the literature that better quality institutions have a positive impact on output, whereas the speed of reforms has a negative impact through the disruption of economic activity. We hypothesize a similar relationship for the speed of institutional reforms and total factor productivity. To date empirical research on this issue is insufficient.

3. Methodology of Estimation

In this paper, we use a non-parametric Malmquist multifactor productivity index as our empirical tool. One of the most important advantages of using this method is that it does not necessitate the assumption of full efficiency. Furthermore, the use of the Malmquist productivity index, instead of a parametric estimation, helps avoid a specification error since there is no need to select a specific functional form for estimation. This is important as Giannakas et al. (2003) show that technological efficiency scores are highly sensitive to the choice of functional form when using a stochastic frontier estimation method. Furthermore, Malmquist does not require behavioral assumptions, which is relevant to transition economies where profit maximization may not be the first goal for all firms, especially government-owned firms. Malmquist also allows departures from constant returns to scale which might be too restrictive. Finally, the Malmquist index can be broken down into technological change and efficiency change, thereby providing further insights into the relative performance of the countries of interest.

The biggest disadvantage of the Malmquist index is that it lacks an error component, thus leaving no room for statistical inference. This problem, however, can be addressed by using a bootstrap method, introduced by Efron (1979).

In the following sub-sections we provide theoretical background for the Malmquist productivity index and describe a bootstrapping procedure.

3.1. Malmquist Productivity Index

The subsequent several paragraphs describe the Malmquist multifactor productivity index following closely the works of Coelli et al. (1997), Färe et al. (1994), and Fulginiti and Perrin (1997). A Malmquist multifactor productivity index is a geometric average of four distance functions, which can be either input- or output-oriented. The former is a measure of inefficiency represented by a scalar by which it is possible to reduce inputs to still be able to produce a specific level of output. An output distance function, on the other hand, is a scalar by which it is possible to increase output for a given level of inputs. The two measures are equivalent only under the constant returns to scale assumption. However,Coelli et al. (1997) point out that assuming a CRS technology is only appropriate when all units are operating at an optimal scale. This is clearly too strict of an assumption for transition economies, and we therefore employ a variable returns to scale (VRS) technology instead.[5] This necessitates the choice between input and output orientation. We adopted the output-distance-function approach because it emphasizes the potential increase in GDP rather than a reduction in the use of inputs.

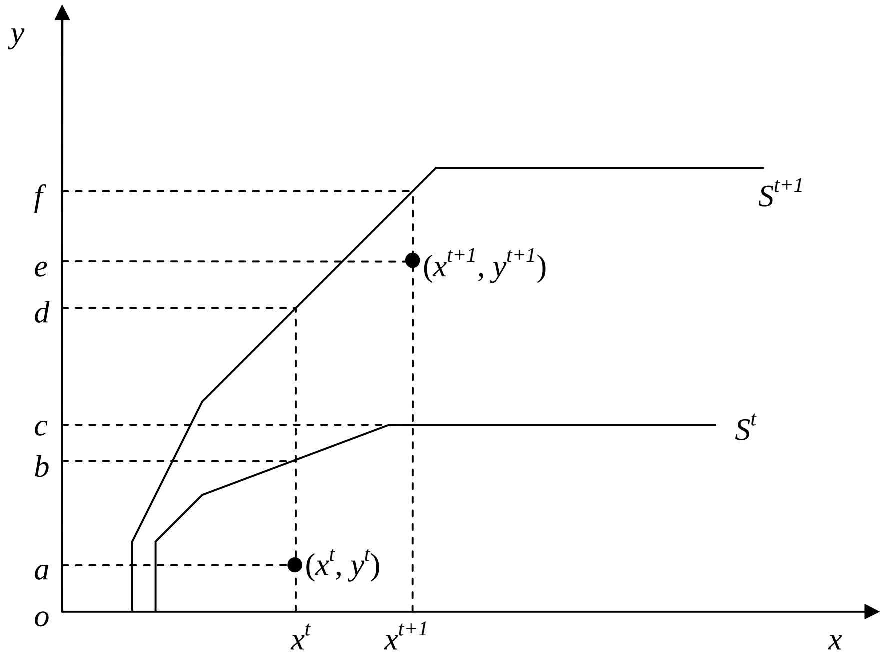
The output distance function $D^t_o(x^t,y^t)$ at time t is the ratio of a current (observed) output y^t to the maximum achievable multiple of that current output for the given quantity of inputs x^t over a technology set S^t. Formally,

$$D_o^t(x^t, y^t) = \inf\left\{\theta : \left(x^t, \frac{1}{\theta} y^t\right) \in S^t\right\}. \quad (1)$$

[5] Grifell-Tatjé and Lovell (1995) note that Malmquist estimates turn out systematically biased when one applies the VRS assumption to data characterized by non-constant returns to scale. However, using CRS does not solve the problem since CRS gives an accurate measure of TFP change only if the true technology is CRS in both periods, which is not applicable to our case.

In the following figure, $D^t_o(x^t,y^t)$ is *oa/ob*.

Figure 1. Output distance function for time periods *t* and *t+1*.



Since the input-output bundle (x^t,y^t) lies below the potential frontier, this ratio is less than one, and (x^t,y^t) is said to be Farrell- inefficient. If in the next period a producer is at point (x^{t+1},y^{t+1}), then the distance function $D^t_o(x^{t+1},y^{t+1})$ is *oe/oc*, or the ratio of the observed output *e* at *t+1* with input x^{t+1} to the maximum potential output *c* on the technological frontier of the previous period, S^t. Clearly, (x^{t+1},y^{t+1}) is infeasible with technology S^t, and $D^t_o(x^{t+1},y^{t+1})$ is greater than one. Allowing a change in technology (here, a positive shift of the production frontier from S^t to S^{t+1}), we can obtain two more distance functions. The latter are different from the ones described above only in their reference technology. That is, they compare the observed input-output bundles to the potential for technology S^{t+1}. Hence, $D^{t+1}_o(x^t,y^t)$ is *oa/od* and $D^{t+1}_o(x^{t+1},y^{t+1})$ is *oe/of*.

Based on the work of Caves, Christensen and Diewert (CCD, 1982), Färe et al. (1994) propose the following formulation of the Malmquist index

$$M\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \frac{D_o^{t+1}(x^{t+1}, y^{t+1})}{D_o^t(x^t, y^t)} \times \left[\frac{D_o^t(x^{t+1}, y^{t+1})}{D_o^{t+1}(x^{t+1}, y^{t+1})} \cdot \frac{D_o^t(x^t, y^t)}{D_o^{t+1}(x^t, y^t)}\right]^{\frac{1}{2}}, \qquad (2)$$

where the expression outside the brackets represents efficiency change and the rest is technological change. In the notation of Figure 1, this Malmquist index can be stated as

$$M\left(x^t, y^t, x^{t+1}, y^{t+1}\right) = \frac{oe/of}{oa/ob} \times \left[\frac{oe/oc}{oe/of} \cdot \frac{oa/ob}{oa/od}\right]^{\frac{1}{2}} = \frac{oe/of}{oa/ob} \times \left[\frac{of}{oc} \cdot \frac{od}{ob}\right]^{\frac{1}{2}}. \qquad (3)$$

3.2. Bootstrapping Malmquist

As noted, the most important disadvantage of the Malmquist index is that it ignores measurement errors and other noise and, consequently, does not allow for statistical inference. Luckily, this problem can be addressed with bootstrapping.[6] Simar and Wilson's (1998, p. 49) note that

> [t]he bootstrap introduced by Efron (1979) seems an attractive tool to analyze the sensitivity of measured efficiency scores to sampling variation. Bootstrapping is based on the idea of repeatedly simulating the data-generating process (DGP), usually through resampling, and applying the original estimator to each simulated sample so that resulting estimates mimic the sampling distribution of the original estimator.

Löthgren and Tambour (1999) provide a step-by-step procedure for bootstrapping Malmquist, reproduced here for the reader's convenience with a correction in Step 4 (see Simar and Wilson, 2000).

Step 1: Let $\hat{D}^t_{o,j}(x^t_j, y^t_j)$ be an estimate[7] of the output distance function for a country j at time t. Then, given the above definition of distance functions, the following must be true

$$(x^t_j, \hat{y}^{t,f}_j) = (x^t_j, (\hat{D}^t_{o,j})^{-1} y^t_j), \tag{4}$$

where x^t_j and y^t_j are the input and output observations for country j at time t, respectively, and $\hat{y}^{t,f}_j$ is an estimate of the unobservable frontier output.

Step 2: From the set of estimates of the original distance functions ($\hat{D}^t_{o,j}$, j = 1,…, J) resample with replacement J distance functions, save them in vector $\underline{D}^{*t} = D^{*t}_1,...,D^{*t}_J$, and let Γ^{*t} denote a ($J\times1$) vector of resampled country indices.[8]

Step 3: Substituting D^{*t}_j for $\hat{D}^t_{o,j}$ in equation (4) and rearranging yields bootstrap pseudo-observations

$$(x^t_j, y^{*t}_j) = (x^t_j, D^{*t}_j\ \hat{y}^{t,f}_j). \tag{5}$$

Step 4: Using the pseudo-observations from Step 3 we calculate a new enveloping frontier. The bootstrap distance functions $\hat{D}^{*t}_{o,j}(x^t_j, y^{*t}_j)$ are then calculated as the distance of each country's original observation (x^t_j, y^t_j) to the new bootstrap frontier.[9] Estimation of the other three distance functions, one for time t+1 and two for the cross-periods, can be done in a similar fashion.

Step 5: Repeat steps one through four 1000 times to generate a set of 1000 country-specific bootstrapped Malmquist indices[10]

$$\hat{M}^{*b}_{o,j} = \frac{\hat{D}^{*b,t+1}_o(x^{t+1}_j, y^{*b,t+1}_j)}{\hat{D}^{*b,t}_o(x^t_j, y^{*b,t}_j)} \times \left[\frac{\hat{D}^{*b,t}_o(x^{t+1}_j, y^{*b,t+1}_j)}{\hat{D}^{*b,t+1}_o(x^{t+1}_j, y^{*b,t+1}_j)} \cdot \frac{\hat{D}^{*b,t}_o(x^t_j, y^{*b,t}_j)}{\hat{D}^{*b,t+1}_o(x^t_j, y^{*b,t}_j)} \right]^{\frac{1}{2}}, \tag{6}$$

where b = 1, …, 1000, and, as before, the first term on the right-hand side is efficiency change and the second term is technological change. Löthgren and Tambour (1999, p. 420) set $\Gamma^{*b,t} = \Gamma^{*b,t+1} = \Gamma^{*b}$ "to keep the [country]-specific dynamic structure of productivity over time."

The bootstrap procedure discussed so far is known as the naïve bootstrap, because it draws samples from a discrete population. Since the underlying probability density function is continuous, the naïve bootstrap

[6] Semenick Alam (2001) notes that one can also rely on the central limit theorem to derive asymptotic confidence intervals. However, this approach is not reliable for small samples.

[7] A linear programming algorithm for estimation is given in Löthgren and Tambour (1999).

[8] Draws for each group of transition economies were made from the pool of original distance functions of each respective group.

[9] This is in contrast to Löthgren and Tambour (1999), who calculate the bootstrap distance functions as the distance from the pseudo-observations for each country to the new enveloping frontier.

[10] MacKinnon (2002) notes that the number of simulations should be greater than 999 to reduce the loss of power to an acceptable level.

will provide an inconsistent estimator. To improve the estimator, we smooth the bootstrap as outlined in Ray (2004).

In this paper we use the Gaussian smoothing, which implies using the standard normal density function ϕ as the kernel function:

$$\hat{f}(t) = \frac{1}{nh}\sum_{j=1}^{n}\phi\left(\frac{t-\hat{D}_{o,j}}{h}\right), \tag{7}$$

where h is a smoothing parameter, and n is the number of elements in the sample of distance functions. Due to the nature of distance functions, $\hat{D}_{o,j}$ can only take on values of one or above. However, the smoothing procedure may result in smoothed bootstrap values of $\hat{D}_{o,j}$ that are lower than one. To solve this problem, the smoothing procedure can be modified by using a negative reflection method proposed by Silverman (1986):

$$\hat{f}(t) = \frac{1}{2nh}\sum_{j=1}^{n}\left[\phi\left(\frac{t-\hat{D}_{o,j}}{h}\right)+\phi\left(\frac{t-2+\hat{D}_{o,j}}{h}\right)\right]. \tag{8}$$

The new smoothed bootstrap sample, $D^{**}_{o,j}$, will then be generated by

$$D^{**}_{o,j} = \begin{cases} D^{*}_{o,j} + h\varepsilon_j & \text{if } D^{*}_{o,j} + h\varepsilon_j \le 1 \\ 2-\left(D^{*}_{o,j} + h\varepsilon_j\right) & \text{otherwise} \end{cases}, \tag{9}$$

where ε is drawn at random from the standard normal distribution. As suggested by Silverman (1986) and Ray (2004), we choose the smoothing parameter as:

$$h = 0.9An^{-\frac{1}{5}}, \tag{10}$$

where $A = min$ [standard deviation of $\hat{D}_o$, interquartile range of $\hat{D}_o/1.34$].

To obtain an asymptotically correct variance of the bootstrap sample, the generating process of D^{**} is further modified as outlined in Dong and Featherstone (2004):

$$\tilde{D}^{**}_{o,i} = \frac{1}{\mathrm{n}}\sum_{\mathrm{j=1}}^{\mathrm{n}} D^{*}_{o,j} + \frac{1}{\sqrt{1+b^2/\hat{\sigma}^2_{\hat{D}}}}\left(D^{**}_{o,j} - \frac{1}{\mathrm{n}}\sum_{\mathrm{j=1}}^{\mathrm{n}} D^{*}_{o,j}\right). \tag{11}$$

Once we get our 1000 smoothed bootstrap Malmquist indices, we can create confidence intervals to obtain statistical significance for Malmquist scores and its components. Following Mooney and Duval (1993), the 100(1 – α) percent confidence interval is constructed by ordering the bootstrap distance functions according to their size and cutting off the top and bottom 1000(α/2) estimates of the bootstrap distance functions.

Simar and Wilson (2000) show that the distance function estimators are biased and suggest that a correction for bias is needed if $\hat{\sigma}^2 < (1/3)[1000^{-1}\sum_1^{1000}\tilde{D}^{**}_{o,j} - \hat{D}_{o,j}]^2$, where $\hat{\sigma}^2$ is the variance of $\tilde{D}^{**}$. Therefore, for estimates that satisfy this condition we calculate a bias-corrected (BC) confidence interval based on Mooney and Duval (1993) and Efron and Tibshirani (1993).[11] To calculate the BC confidence interval we use the median bias to center the bootstrap distribution $\hat{F}^*(\tilde{D}^{**})$ around the population distance function parameter D.[12] The median bias z_0 is the difference between the median of $\tilde{D}^{**}$ and $\hat{D}$

[11] An alternative bias-corrected and accelerated method is described in Atkinson and Wilson (1995).
[12] Strictly speaking, confidence intervals are constructed around the bootstrapped Malmquist and its components, rather than distance functions. Here, we use the latter to avoid introducing more notation.

in normal units. The lower BC endpoint is thus the value of $\tilde{D}^{**}$ at the $[\Phi(2z_0 + z_{\alpha/2})]\times 100$ percentile, whereas the upper BC endpoint is the value of $\tilde{D}^{**}$ at the $[\Phi(2z_0 + z_{1-\alpha/2})]\times 100$ percentile.

4. Country Classification

To carry out the empirical comparison of the two reform strategies using Malmquist, we have split our sample of countries into gradual, intermediate, and radical reformers. The classification into these three groups was made on the basis of the indices for the pace of reforms developed by de Melo et al. (1996). This procedure inevitably carries a degree of arbitrariness since any index of institutional quality must incorporate subjective measures. However, a high correlation of various measures of political and institutional environment indicates that the subjective rankings of countries are consistent across experts and, therefore, are reasonably reliable (Havrylyshyn and van Rooden, 2000).

De Melo et al. (1996) construct a cumulative liberalization index (*CLI*) based on a weighted average of various elements of reforms, such as price liberalization and de-monopolization of state enterprises, relaxing foreign trade restrictions, privatization, and restructuring of the banking system. Since we are concerned with the speed of reforms, rather than their level, we take the sum of the three largest annual changes in *CLI* between 1989 and 1994 for each country and rank the countries according to the results, as presented in Table 1 in the appendix. The ordered index in Table 1 was divided into five classes, each having a “width” of .146. The top two classes (index between .130 and .422) were categorized as the countries with gradual reforms, the bottom two classes (index between .568 and .860) were classified as the Big Bang reformers, and the middle class was labeled as the intermediate group.

5. Data

The calculation of the Malmquist productivity index requires output and input quantity data. Such data were collected for a sample of twenty-two transition economies.

Output quantities were proxied by the GDP figures in constant 2000 US dollars, obtained from the World Development Indicators (WDI) online database. An alternative to this proxy is GDP measured in international dollars based on purchasing power parity rates. The distinction between these two measures of output is of little importance here because we compare the performance of countries across time and not their level of development at a given point in time. The GDP figures based on constant 2000 US dollars were chosen because the data for constructing our capital input were available only in this measure of prices.

Capital and labor were applied as inputs. The stock of capital, K, was computed following Easterly and Levine (2001). Countries were assumed to be in their respective steady states in the initial year. Therefore, the capital-output ratio, $k = K/GDP$, can be described by $k = i/(g + \delta)$, where $i = I/GDP$ is the observed ratio of investment I (proxied by the WDI gross fixed capital formation in constant 2000 US dollars) to output, δ is the rate of depreciation assumed to equal 0.07, and g is the weighted average of the growth rates of real output in each country and the World. More specifically, g is computed as $0.75*g_w + 0.25*g_i$, where g_w is the WDI average annual growth rate of real GDP of 175 countries between 1991 and 1995 and g_i is the WDI average annual growth rate of real GDP of the given transition country i between 1991 and 1995.[13] Finally, after obtaining the initial capital stock, the capital stock for the subsequent years was found according to $K_{t+1} = K_t(1 - \delta) + I_t$.

The labor input was derived from the WDI total labor force data. To account for the differences in the general skill level, labor was augmented by literacy rates, acquired primarily from the WDI database and

[13] Following Easterly and Levine (2001), the 0.75 and 0.25 weights and the period of 1991-1995 were selected in order to reduce the influence of business cycles.

the CIA World Factbooks. Missing values were extrapolated using the average annual growth rates of the original observations.

Before proceeding to the following section, a word of caution is appropriate. The data were collected on the aggregate level and as such are prone to measurement and conceptual errors. Variables are defined differently across countries, leading to reduced comparability and potentially significant biases (Fischer et al., 1996). Furthermore, exchange rates and prices generally differ from equilibrium prices and therefore make inter-country comparisons difficult. Taking averages across countries within each category should alleviate these problems to some degree and help provide meaningful results.

6. Results

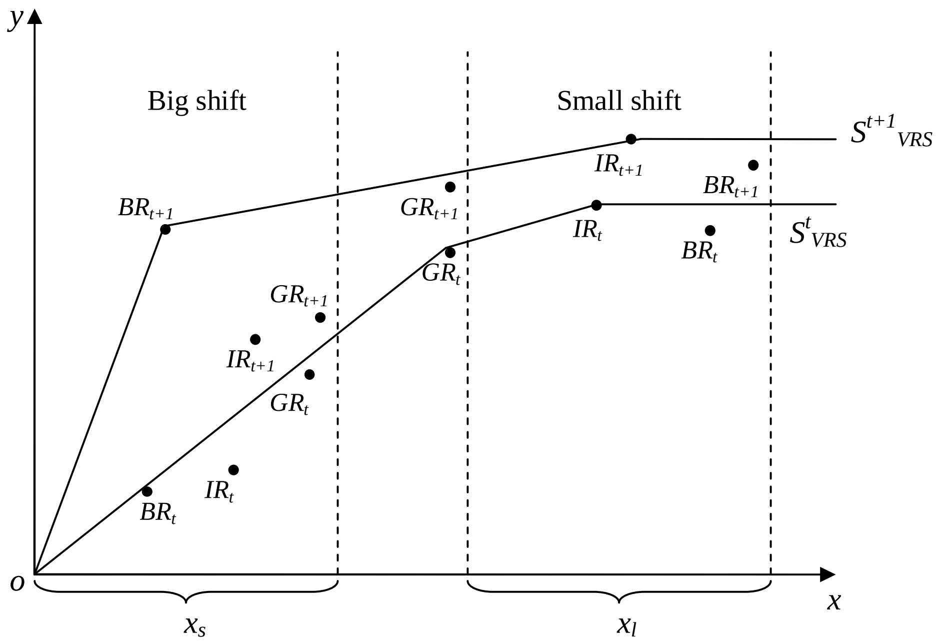
The results discussed in this section are based on the regional technological frontier. That is, our definition of "new knowledge" includes, in addition to the new discoveries made in transition economies, the know-how that was already available to the industrialized world, but was not previously known within our sample of countries. However, for robustness we ran an additional estimation of the Malmquist using the world technological frontier by including a number of industrialized countries to account for a more broad definition of "new" knowledge. The results were mostly consistent to those with the regional technological frontier. Also, some researchers classify China as a transition economy. We opted for excluding China from our discussion due to it being too distinct from the rest of the countries in the sample. Estimating the Malmquist with China did not materially alter our results.

The results of our non-parametric production frontier analysis are summarized in Table 2 in the appendix. We compare productivity performance of the three types of transition economies – Big Bang, gradual, and intermediate reformers – by reporting the differences of the averages of their Malmquist, technological change, and efficiency change scores. In order to see how transition economies fared relative to each other during the time of the most fundamental reforms compared to thereafter, we split our sample time period in two. The last row of the table shows the results for the entire time period.

During the initial 1990-1996 time period of most active reforms (with some lag), none of the three groups of countries exhibited a statistically significant advantage in terms of technological change. In fact, the differences in technological change scores were insignificant for all time periods and reform strategies with one exception: Big Bang reformers had a higher technological progress than gradual reformers during the 1996-2007 period at the 10% level of statistical significance. This lack of technological dominance of any one of the reform groups may be related to the way the technological change is calculated in the Malmquist productivity analysis or because of the nature of knowledge dissemination.

As explained above, the technological change in the Malmquist framework is represented by a shift of the production frontier. In Figure 1, the technological change is represented by the square root of the product of *od/ob* and *of/oc* at inputs x^t and x^{t+1}, respectively.

Figure 2. Calculation of Technological Change in the Malmquist Framework.



The magnitude of this shift is unlikely to be uniform. For illustration, let us highlight on the input continuum in Figure 2 an area where input resources are small, x_s, and an area where inputs resources are large, x_l. Among the countries in our sample, Armenia and Estonia belong to the small resources range, while Poland and Russia belong to the large resources range. In our illustration, considerable technological progress occurs in the x_s range, while technology changes only modestly in the x_l range. The big push of the frontier in the x_s range is a result of a single country's success. However, due to the way the Malmquist index is calculated, other countries in the vicinity will display technological change of about the same magnitude even if their actual output growth is very small. Since in our sample an approximately equal number of countries belonging to each group (BR, GR, and IR)[14] happen to be located in any given input range,[15] it is not surprising that the Malmquist estimation provides similar average technological change scores for the three groups of transition economies.

Also, the lack of statistically significant differences in technological change may be related to the question of where new knowledge is created. According to the economic growth literature (see Coe et al., 1997; Easterly et al., 1993; Helpman, 1997), most of the new knowledge originates in industrialized countries. The rest of the world tends to duplicate this knowledge rather than spend vast resources on their own research and development. Assuming that all countries engage in some type of reverse engineering it is not surprising that the dissemination of knowledge occurs more or less evenly among the three types of reformers. This implies that the technology frontier moves in a similar fashion for the entire sample; hence, no variation in technological progress. Any differences in overall productivity change arise then from the varying abilities of the countries to absorb the new technology and incorporate it into the production process. This is captured by the efficiency change component of the Malmquist index.

[14] BR, GR, and IR stand for Big Bang, gradual, and intermediate reformers, respectively.
[15] This was confirmed by arranging the transition economies in an ascending order according to both the size of their labor force and the amount of physical capital.

The efficiency change results for the initial 1990-1996 period indicate that the Big Bang countries performed over 20 percent better than gradual reformers at the 10% significance level and better than intermediate reformers, albeit not statistically significantly. In the subsequent eleven-year period, the gradual group displayed a considerable comparative improvement outperforming the Big Bang group by almost 67 percent at the one percent significance level and the intermediate group did better than the Big Bang reformers by 23 percent at the 10% significance level, rendering Big Bang the worst reform strategy. Possibly, Big Bang's initial comparative success was due to the quick elimination of inefficient firms and the rapid growth of new private business enterprises. In the long run, however, the slower, less disruptive pace of reforms in the countries that adhered to a more gradual strategy surpassed the results achieved by the initial boost in the Big Bang transition economies. The differences in efficiency change scores for the full 1990-2007 period, however, did not turn out to be statistically significant, even though the gradual reformers did score higher.

One potential cause for concern regarding relative efficiency changes is that it is possible that countries that start off the transition process at the lower level of efficiency catch up at a faster pace. This is akin to the idea of conditional convergence in the Solow growth model. On a technical level, this may happen because efficiency change is defined in the Malmquist index as the ratio of new efficiency to initial efficiency (see equation 2). Countries with a lower efficiency base will display higher efficiency change scores despite similar absolute changes. It turns out that there is a systematic difference among the speed-of-reform groups that we consider, as the gradual reformers are on average much less efficient to begin with than either the intermediate or Big Bang reformers. The fact that initial conditions may play an important role is also vastly supported in the literature (see, for example, Heybey and Murrell, 1997; Eicher and Schreiber, 2005; De Melo et al., 1997; Berg et al., 1999; Havrylyshyn and van Rooden, 2000; Svejnar, 2002; Fischer and Sahay, 2004, and Popov, 2000 and 2007). There is disagreement, however, over their long term importance. To account for the possibility of a significant effect of the differences in the starting position of each country, we incorporate the distance functions for 1990 as a measure of initial inefficiency in the estimation. We found that accounting for the initial level of efficiency did not change our previous conclusions. This is a further indication of the robustness of our results.

In terms of total factor productivity change, the Big Bang reformers clearly outperformed the other reformers during the initial 1990-1996 period, while the gradual reformers had the worst performance. All results for this time period are highly significant. Interestingly, the picture of comparative productivity performance is completely reversed in the second sub-period. The gradualists did over 51 percent better than Big Bang and 41 percent better than the intermediate group, while the latter outperformed Big Bang by over ten percent. All of these results are also significant at the 1% level.

Overall, for the entire time period, the gradual reform strategy has yielded the best results with highest (and statistically significant) Malmquist productivity scores. The difference between the Malmquist scores of Big Bang and intermediate reformers was not statistically significantly.

Figure 3 in the appendix shows the average annual technological change, efficiency change, and Malmquist scores for each group during the entire 1990 – 2007 period. As expected, positive technological change began occurring one to two years earlier than improvements in efficiency. The Malmquist index prior to 1994 was below one, indicating a productivity decline in transition economies in the early years. The average annual productivity improvement in the subsequent years fluctuated around three percent. This figure also shows that the shock therapy produced larger improvements in total factor productivity during the early years of transition than the other two strategies, while gradual change became more successful in the more recent years.

7. Discussion

The vast majority of papers that compare radical and gradual reform strategies were written in the early and mid-nineties. However, only now enough time has passed to allow empirical analyses to go beyond the very short term. This paper uses 17 years of transition experience and provides new insights into the comparison of alternative courses for reforms. This is not only important for improving our understanding of past performance, but it may also provide valuable advice to the remaining non-market economies and, more generally, to less developed countries.

Unlike most studies in this area of research that examine the effect of the speed of reforms, we estimate improvements in total factor productivity, technological change, and efficiency change instead of the growth rate of per capita GDP. The analysis of these determinants of economic growth provides a better picture of the long-run growth prospects than the changes in current GDP per capita. For estimation we employ a data envelopment analysis technique. While there are several papers that have used the Malmquist method in the context of transition economies, few use bootstrapping to obtain statistical confidence for their estimated results. To incorporate the bootstrap procedure into the calculation of the Malmquist scores, we have developed an original programming code for GAMS (available upon request), as computer programs that simultaneously estimate Malmquist and its bootstrap are not readily available.

The results of our analysis suggest that in the long run the gradual reform strategy was superior in terms of growth of productivity and its components. Initially, Big Bang reformers performed stronger, but this is probably due to the more drastic cut of unproductive inputs rather than an increase in the efficiency of the existing inputs. This interpretation is consistent with the conventional wisdom that a shock-therapy reform produces an initial disruption of the economy and, despite increases in productivity, decreases economic output. During the more recent years of transition, the gradual approach turned out to be significantly more effective, such that it appeared to be the best strategy for the overall 1990-2007 period. This points to the importance of considering a long enough time horizon when evaluating the performance of reform policies.

These findings have important implications for the optimal choice of reform strategy for less developed countries and the remaining non-market economies. A gradual reform not only alleviates the initial disruption of output, but also leads to higher productivity gains after a few years, compared to a more radical reforms strategy. Increased productivity leads to increased international competitiveness, which is the path to long run growth.

Table 1. Country rankings according to speed of reforms indices.

Countries	**Index of Speed of Reforms**	
Belarus	0.29	**Gradual Reformers**
Azerbaijan	0.31	
Georgia	0.31	
Ukraine	0.32	
Kazakhstan	0.35	
Slovenia	0.37	
Armenia	0.38	
Croatia	0.38	
Uzbekistan	0.39	
Hungary	0.44	**Intermediate Reformers**
Moldova	0.47	
Romania	0.49	
Bulgaria	0.53	
Latvia	0.54	
Russia	0.56	
Poland	0.58	**Big Bang Reformers**
Estonia	0.62	
Lithuania	0.65	
Albania	0.70	
Kyrgyzstan	0.72	
Czech Republic	0.86	
Slovakia	0.86	

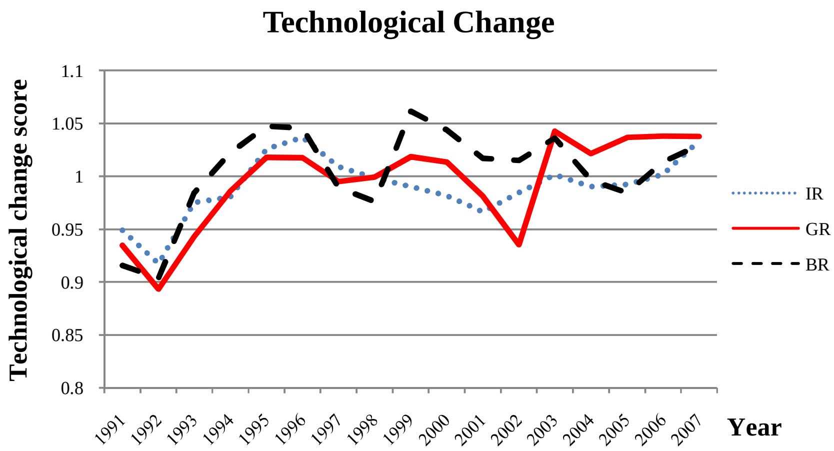
Table 2. Comparative productivity performance of Big Bang, Gradual, and Intermediate reform strategies

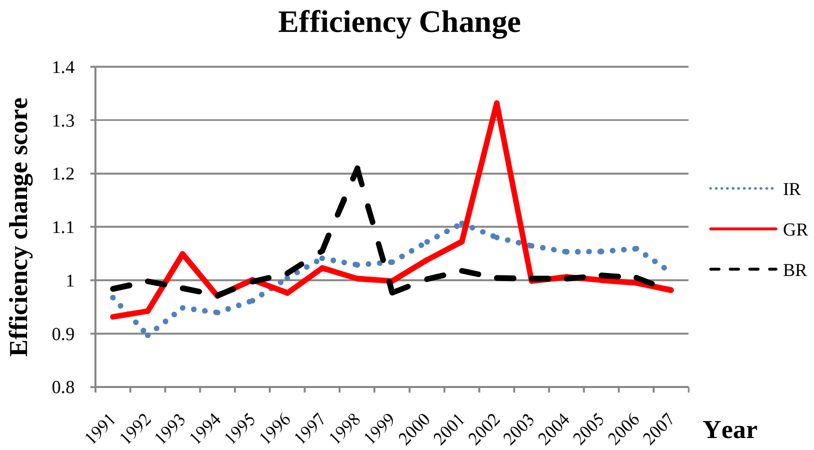
	Technological Change			**Efficiency Change**			**Malmquist Total Factor Productivity Index**		
	GR-BR	**GR-IR**	**BR-IR**	**GR-BR**	**GR-IR**	**BR-IR**	**GR-BR**	**GR-IR**	**BR-IR**
1990 – 1996	0.0182	0.0739	0.0557	-0.2014*	-0.1112	0.0902	-0.1858***	-0.0478***	0.1380***
1996 – 2007	-0.1631*	-0.1251	0.0380	0.6684***	0.4377	-0.2307*	0.5137***	0.4105***	-0.1032***
1990 – 2007	-0.1119	-0.0061	0.1058	0.1568	0.1779	0.0211	0.0874**	0.1963***	0.1089

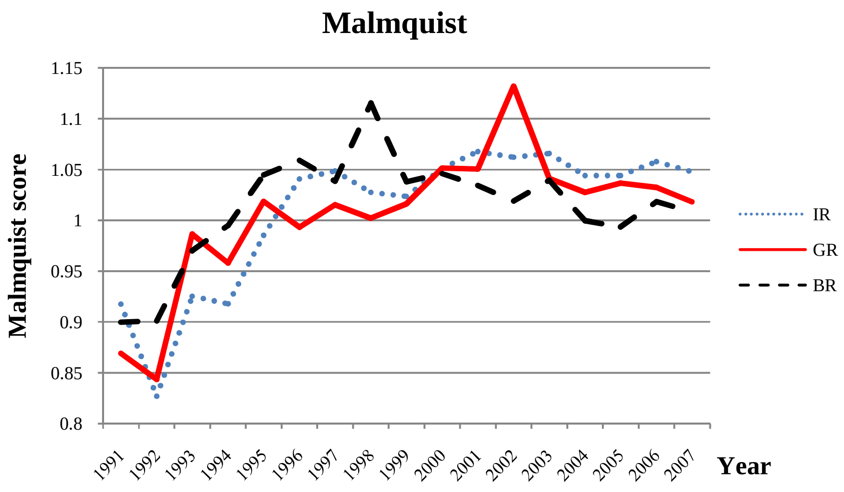
*** significant at 1% level, ** significant at 5% level, * significant at 10% level.

The reported values are differences in technological change, efficiency change, and Malmquist scores for Big Bang reformers (BR), Gradual reformers (GR) and Intermediate reformers (IR). To get a single number for productivity scores for each of these three groups of countries, we averaged individual country scores within their respective groups. Simar and Zelenyuk (2007) suggest a weighted arithmetic average. Since our interest lies in the effect of the speed of reforms on individual countries as units, we use a simple arithmetic average, instead. Values are for the whole time period, not annual averages.

Figure 3. Annual Technological Change, Efficiency Change, and Malmquist Scores (group averages, 1990-2007, all countries)






Malmquist
Malmquist score
1.15
1.1
1.05
1
0.95
0.9
0.85
0.8
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
Year
IR
GR
BR

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