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Concerning Technology Adoption and Inequality

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Abstract:

Empirical evidence suggests that there has been a divergence over time in income distributions *across* countries and *within* countries. Furthermore, developing economies show a great deal of diversity in their growth patterns during the process of economic development. For example, some of these countries converge rapidly on the leaders, while others stagnate, or even experience reversals and declines in their growth processes. In this paper we study a simple dynamic general equilibrium model with household specific costs of technology adoption which is consistent with these stylized facts. In our model, growth is endogenous, and there are two-period lived overlapping generations of agents, assumed to be heterogeneous in their initial holdings of wealth and capital. We find that in a special case of our model, with costs associated with the adoption of more productive technologies fixed across households, inequalities in wealth and income may increase over time, tending to delay the convergence in international income differences. The model is also capable of explaining some of the observed diversity in the growth pattern of transitional economies. According to the model, this diversity may be the result of variability in adoption costs over time, or the relative position of a transitional economy in the world income distribution. In the more general case of the model with household specific adoption costs, negative growth rates during the transitional process are also possible. The model's prediction that inequality has negative impact on technology adoption is supported by empirical evidence based on a cross country data set.

Keywords: inequality, technology adoption, international income differences, altruism, negative growth rates.

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1. Introduction

Empirical evidence suggests that there has been a divergence over time in income distributions *across* countries and *within* countries. For example, based on the work of Quah (1996, 1997), there is strong evidence to suggest an emergence of "twin-peaks" in cross-sectional world income distributions. There is also substantial evidence to suggest that this type of polarization is present in income distributions within countries. (See, for example, Sala-i-Martin 2006, Jappelli and Pistaferri 2000, Piketty and Saez 2003, and Schluter 1998, among others). Typically the empirics of economic growth support Baumol's (1986) idea of "convergence clubs" emerging across and within countries.

Furthermore, Pritchett (1997) suggests that the growth patterns of countries that fall into the "developing economies" category exhibit a great deal of diversity. For example, some of these countries converge rapidly on the leaders, while others stagnate, or even experience reversals and declines in their growth processes. Pritchett cites the experience of Mozambique (-2.2 percent per annum), and Guyana (-0.7 percent per annum), as examples from a group of 16 developing economies which experienced negative growth rates in the period 1960 – 1992.

There is a large theoretical and empirical literature that seeks to explain cross country income differences (For a collection of representative literature see Acemoglu 2004a, 2004b.). An interesting strand within this literature looks at the implications of technology adoption and the consequent structural change associated with the process of growth and development. Recent efforts in this direction, (e.g., Hansen and Prescott, 2002, Ngai, 2004, Greenwood and Jovanovic, 1990, Parente and Prescott, 2004), suggest barriers to adopting more productive technologies as an explanation for cross-country income differences. There are studies that also suggest that inequalities in initial income distributions have a bearing on the issue of technology adoption. For example, in the work of Horii et al.(2005) credit market imperfections, in conjunction with inequality prevents the adoption of more capital intensive technologies. In a model with an exogenous, fixed cost of adopting technology, Khan and Ravikumar (2002), show that income inequality within a country increases over time.

The model of this paper is similar in sprit to the literature on technology adoption discussed above. In particular, the model has features in common with the framework used in Khan and Ravikumar (2002) in that it uses an "AK" specification for technologies used, and has a fixed cost associated with adopting more productive technologies. However, in contrast to their model, we use a two-period overlapping generations structure, which means that while a generation is faced with a one-time cost of adoption, the dynasty to which the household belongs faces the adoption decision in each time period. Furthermore, we allow for variability in adoption costs across households and over time.

As in Khan and Ravikumar, in our model there is a threshold level of capital for which the households in the economy switch to the more productive technology. The threshold level of capital depends on the parameters of technology, and is monotonically declining in the level of wealth of the household, a feature that is consistent with empirical evidence. (See for example, Wozniak 1987, Alauddin and Tisdell, 1991). Furthermore, unlike Khan and Ravikumar this threshold also depends on preference parameters. For example the degree of altruism seems to matter in our model. More altruistic households are likely to adopt the better technology sooner and quicker adoption reduces post-transitional inequality.

We first consider a special case of the model in which adoption costs do not vary across households but are allowed to vary over time in some of our numerical experiments. We find that assumptions about the initial distribution can have very different implications for the date in which all households in the economy adopt the better technology. Higher the initial level of inequality later is the date of complete adoption of the better technology. We also empirically test this result of the model using a cross country data set, and find some empirical support for this result. Inequality can therefore increase and remain persistent for very long periods of time, consequently delaying the process of structural transformation that is associated with development.

It also appears that a higher degree of altruism enables complete adoption to take place sooner as more altruistic households leave larger bequests for the next generation. Post transitional inequality is then decreasing in the degree of altruism, as poorer households tend to leave a larger proportion of their income in the form of bequests. This feature of our model is also consistent with the empirical findings of Tomes (1981).

Also, as mentioned above, we conduct some thought experiments which allow some variability in the *fixed* cost of adoption across different time periods. Our experiments indicate that either *variable* or *increasing* adoption costs delay the process of transition to higher growth rates. Variability in adoption costs also has the effect of producing "*reversals*" in the growth process, a characteristic that has been observed in the case of several developing economies. However, these reversals are not characterized by negative growth rates – a feature that has characterized the growth experience of some developing economies. (See for example Pritchett 1997).

An interesting feature of the model revealed by our experiments is the diversity of growth patterns observed for different cohorts of households in the economy. Household dynasties positioned at the "rich", "poor", or median levels of the income distribution are all capable of experiencing reversals in the growth of income over time. The timing of these reversals, which are temporary, appears to be related to the timing of technology adoption, which is, of course, different across various income groups.

Next, we consider the more general case of the model in which adoption costs are household specific. That is, we allow for adoption costs that vary randomly across households and over time. Our results do not significantly differ from the previous case of fixed adoption costs. However an appealing feature of the general case of our model is that it is capable of producing *negative* growth rates during the transition process. As noted earlier, reversals in the form of negative growth rates is one of the aspects that characterizes the diversity of experiences with the group Pritchett (1997) refers to as "developing economies".

In the section that follows we describe the economic environment. Section 3 presents the results based on various numerical simulations of this model. In section we 4 present the empirical study and the results. Section 5 concludes.

2. The economic environment

The economy consists of two-period lived overlapping generations of agents who are heterogeneous in their holdings of wealth and capital, and have perfect foresight. Time is discrete, with t = 0, 1, 2, …, and we assume that the *initial* distributions of capital and wealth are described by F(.), and G(.) respectively. There are N agents in the economy, and preferences of i^{th} agent born in period *t* are described as follows:

$$U(C_{it}, C_{it+1}, W_{it+1}) = \ln(C_{it}) + \beta \ln(C_{it+1}) + \beta\theta \ln(W_{it+1}). \qquad (1)$$

Here, C_{it} and C_{it+1} denote the agents' consumption in the first and second period of life, W_{it+1} represents bequests left to the next generation. In order to produce output individuals have to decide on adoption of one of two technologies, which will be henceforth referred to as Technology A and Technology B. Technology A is associated with lower productivity but does not involve any adoption costs. It is given by

$$Y_{it}^{A} = AK_{it},$$

where K_{it} represents the period *t composite human and physical capital stock* held by i^{th} old agent and supplied to the young for production. However given that our model has "AK" structure, the nature of this variable has to be interpreted carefully. One can think of K_{it} as an "operational bequest" from the older generation to the young generation. We can, for example, think K_{it} as including physical capital stock in the form of a family owned factory and also including human capital stock in the form of the education and know-how associated with the existing technology. When agents are young they spend K_{it+1} which can be interpreted as the amount paid for the physical capital stock plus training and education required to operate the technology for the next period's young generation. In that sense it may perhaps be more appropriate to interpret each household in our model as a "country" or a "region".

Technology B is more productive than Technology A, but involves a cost of adoption. It is therefore characterized by

$$Y_{it}^{B} = BK_{it} - \delta_{it}, \qquad B > A, \quad \delta_{it} > 0.$$

where δ_{it} represents household specific cost of adopting Technology B. Here δ_{it} represents the household specific adoption cost experienced in period *t*. We assume that this cost is a stochastic shock that is observed by the household prior to making the technology adoption decision. In the subsequent sections of this paper we also consider a special case of the model in which the adoption cost is a fixed, economy-wide cost ($\delta_{it} = \delta$) rather than a household specific variable cost. As in Khan and Ravikumar (2002), we interpret δ in our model as the present value of "learning by doing" costs associated with the more productive technology.

Households adopting Technology A face the following budget constraints:

$$C_{it}^{A} + K_{it+1}^{A} = AK_{it} + W_{it} \qquad (2)$$

$$C_{it+1}^{A} = (1 + r_{t+1}^{A})K_{it+1}^{A} - W_{it+1}^{A} \qquad (3)$$

Households adopting Technology B, on the other hand, face the constraints:

$$C_{it}^{B} + K_{it+1}^{B} = BK_{it} - \delta_{it} + W_{it} \qquad (4)$$

$$C_{it+1}^{B} = (1 + r_{t+1}^{B})K_{it+1}^{B} - W_{it+1}^{B}. \qquad (5)$$

In the equations above r_{t+1}^{A} and r_{t+1}^{B} refer to the rate of return on capital enjoyed by agents who had adopted technologies A and B respectively when they were young. The superscripts A and B applied to the other variables have an analogous interpretation. Note that the "AK" structure of production functions we have assumed here is typically known to generate non-convergence in incomes across countries. See for example Mankiw, Romer, and Weil, (1992) and references therein.

Note also that the model here has a structure similar to that of Khan and Ravikumar (2002), but with the key difference that we allow for household specific adoption costs, and a two-period overlapping-generations structure has been assumed. Khan and Ravikumar consider an infinite horizon model with non-overlapping generations and a one-time adoption cost, after which the old technology is never used. In our model, each generation faces a technology adoption problem, even if the previous generation belonging to the same cohort had adopted the B technology.

Furthermore, we have an additional state variable in the form of bequests W_{it} left over from the previous generation, which can also cause inequalities to persist over time.

Agents using technology A maximize (1) subject to (2) and (3). The implied optimal plans for consumption, capital accumulation and bequests are:

$$C_{it}^{A} = \frac{1}{(1+\beta(1+\theta))}\left[AK_{it} + W_{it}\right] \tag{6}$$

$$C_{it+1}^{A} = \frac{\beta(1+r_{t+1}^{A})}{(1+\beta(1+\theta))}\left[AK_{it} + W_{it}\right] \tag{7}$$

$$W_{it+1}^{A} = \frac{\theta\beta(1+r_{t+1}^{A})}{(1+\beta(1+\theta))}\left[AK_{it} + W_{it}\right] \tag{8}$$

$$K_{it+1}^{A} = \frac{\beta(1+\theta)}{(1+\beta(1+\theta))}\left[AK_{it} + W_{it}\right]. \tag{9}$$

Likewise we can show that agents who adopt B will have:

$$C_{it}^{B} = \frac{1}{(1+\beta(1+\theta))}\left[BK_{it} - \delta_{it} + W_{it}\right] \tag{10}$$

$$C_{it+1}^{B} = \frac{\beta(1+r_{t+1}^{B})}{(1+\beta(1+\theta))}\left[BK_{it} - \delta_{it} + W_{it}\right] \tag{11}$$

$$W_{it+1}^{B} = \frac{\theta\beta(1+r_{t+1}^{B})}{(1+\beta(1+\theta))}\left[BK_{it} - \delta_{it} + W_{it}\right] \tag{12}$$

$$K_{it+1}^{B} = \frac{\beta(1+\theta)}{(1+\beta(1+\theta))}\left[BK_{it} - \delta_{it} + W_{it}\right]. \tag{13}$$

It is clear that i^{th} agent will adopt technology *B iff*

$$U^{B}(K_{it}, W_{it}, r_{t+1}^{B}) \geq U^{A}(K_{it}, W_{it}, r_{t+1}^{A})$$

Where U^{A} and U^{B} represent the indirect utility functions for agents adopting the *A* and *B* technologies respectively. It is then easy to show that this implies the following:

Proposition 1: *Let* $K_{it}^{*} = \frac{\delta_{it} - (1-\lambda)W_{it}}{B - \lambda A}$, *where* $\lambda = \left(\frac{1+A}{1+B}\right)^{\frac{\beta(1+\theta)}{1+\beta(1+\theta)}}$. *For a given level of wealth* W_{it} *a household will adopt technology B iff* $K_{it} \geq K_{it}^{*}$.

The above proposition defines a threshold level of capital required for a household with wealth W_{it} to find it worthwhile to adopt the more productive technology B. Alternatively we could have defined a threshold level of wealth needed to adopt the B technology for a given level of capital stock. The equations of Proposition 1 in fact define a "adoption-possibilities frontier" represented by a locus of combinations of wealth and capital that make the switch to technology B possible. As illustrated by Figure 1, this frontier shifts to the right in (*K, W*) space as the cost of adoption δ increases. Since $\lambda < 1$, higher levels of wealth are associated with lower levels of the threshold capital stock. The frontier is therefore downward sloping.

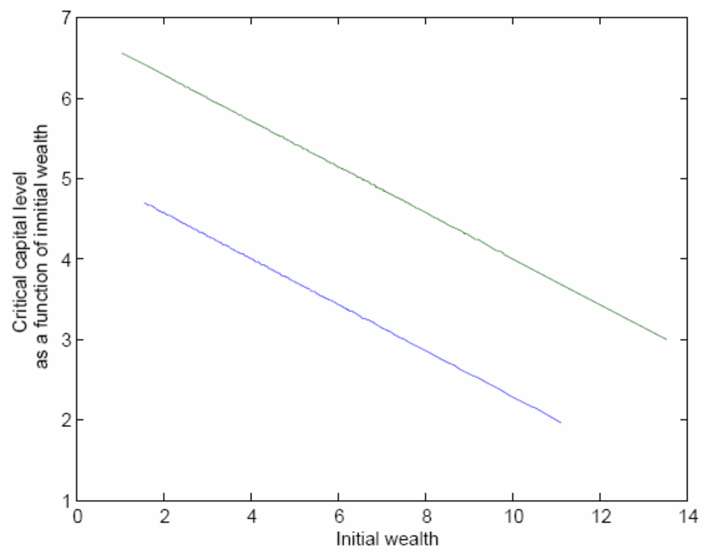

Figure 1: Critical combinations of initial wealth and capital for different levels of adoption costs.

Furthermore, the frontier also depends on preference parameters. Interestingly, a higher value for the altruism parameter (θ) causes a downward shift in the frontier. Intuitively, a more altruistic household is likely to adopt sooner, as this makes it possible to leave larger bequests to the next generation. This has important implications for the dynamics of the model and the evolution of inequality over time, as will be illustrated by some of the numerical experiments conducted in the subsequent section.

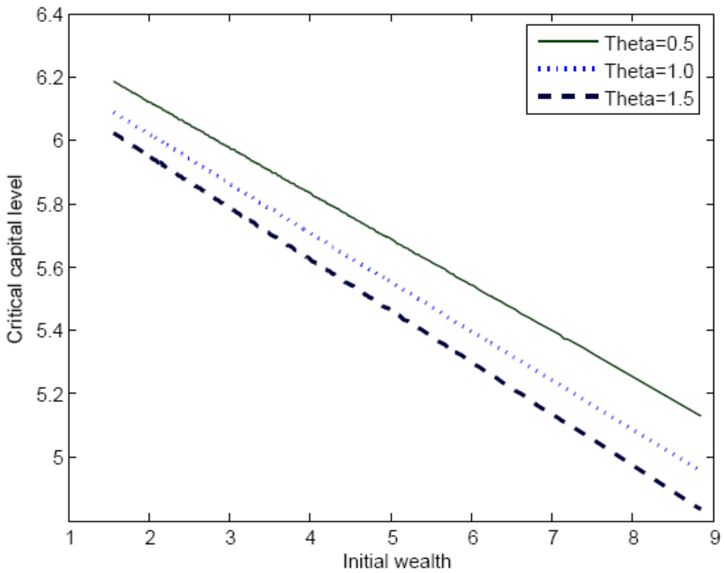

Figure 2: Critical combinations of initial wealth and capital for different levels of altruism parameter (θ).

The dynamics of this model are described by the following system of first order difference equations

$$\left.\begin{aligned} K^A_{it+1} &= \frac{\beta(1+\theta)}{(1+\beta(1+\theta))}\left[AK_{it} + W_{it}\right] \\ W^A_{it+1} &= \frac{\theta\beta(1+r^A_{t+1})}{(1+\beta(1+\theta))}\left[AK_{it} + W_{it}\right] \end{aligned}\right\} for\ K_{it} < K^*_{it}$$

$$\left.\begin{aligned} K^B_{it+1} &= \frac{\beta(1+\theta)}{(1+\beta(1+\theta))}\left[BK_{it} + W_{it} - \delta_{it}\right] \\ W^B_{it+1} &= \frac{\theta\beta(1+r^B_{t+1})}{(1+\beta(1+\theta))}\left[BK_{it} + W_{it} - \delta_{it}\right] \end{aligned}\right\} for\ K_{it} \geq K^*_{it}$$

where $K^*_{it} = \frac{\delta_{it} - (1-\lambda)W_{it}}{B - \lambda A}$, with λ defined as in Proposition 1. Note that the threshold level of capital varies over time, and across households, which makes it difficult to characterize the dynamics of the system analytically.

In what follows, we report results of various numerical experiments that involve varying some of the parameters of the model and the initial distributions of capital and wealth. We focus our attention on the consequences of these experiments for the date of transition to higher growth rates, and the evolution of inequality within the economy over time. An obvious by-product of these experiments is the implication for cross-country income differences and inequality in the world income distribution. We also examine the pattern of growth rates of various aggregates such as savings, per capita output, consumption and bequests over time. These patterns show a significant amount of diversity across different cohorts of households. We therefore also report these patterns for households that are in the lowest 20%, the highest 20%, and the mean and median positions in the income distribution.

3. Results of quantitative experiments

In sub-section 3.1 below we examine the special cases in which (i) the adoption cost is fixed across households and over time ($\delta_{it} \equiv \delta$), and (ii) the adoption cost is fixed across households but allowed to vary over time ($\delta_{it} \equiv \delta_t$). In sub-section 3.2 we examine the more general model with household specific adoption costs.

3.1. Adoption Costs Fixed Across Households

We first examine the implications for the transition process of the economy towards the adoption of Technology B. The combination of parameters is represented in Table 1 below:

The total number of household in the sample is 501.[1] In Figure 3 we report how the number of households adopting Technology A, and the number adopting Technology B, evolve over time. For example the number of households adopting Technology B is represented by the increasing sequence of 2, 32, 129, 287, 420, 478, 495, and 501. The initial distributions of capital and wealth are assumed to be lognormal with mean 3.6 and variance 1.2, with the adoption cost parameter $\delta_{it} \equiv \delta \equiv 20$. In Figure 3 it is clear that all households adopt technology at date $T^* = 8$. Note that our model has a two-

[1] Results do not change qualitatively for larger samples – i.e. the date at which all households adopt B seems to be invariant to the number of households in the initial distribution. Note that since we do not have population growth in this model, the total number of households remains constant over time.

period overlapping-generations structure in which a single period is interpreted as approximately 35 years. (See for example Hansen and Prescott, 2002). Effectively, therefore, this means that the households completely adopt Technology B in 280 years.

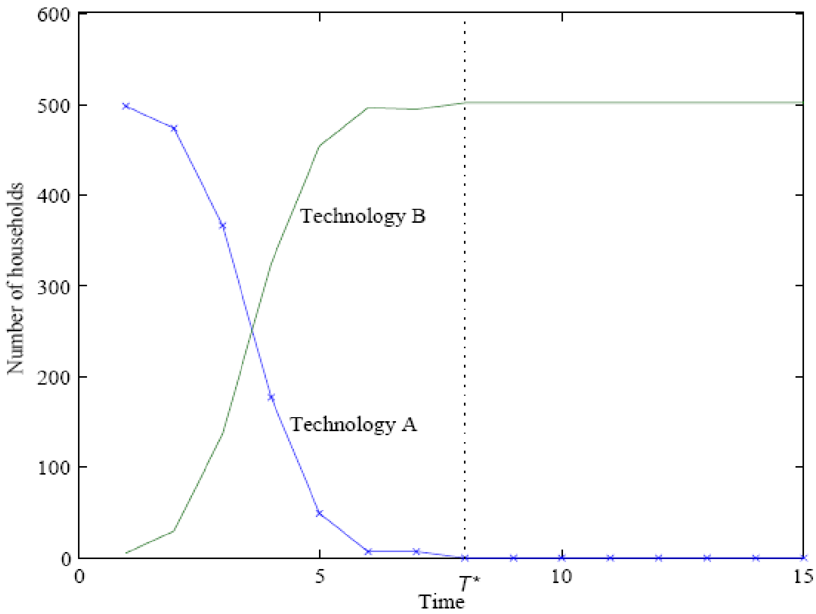

Figure 3: Number of households adopting Technology A or B in different time periods.

3.1.1. Experiments with the adoption-cost parameter δ

In Figure 3 we examine the effect of increasing the fixed cost of adoption on the date at which all households shift to using Technology B. We consider values of δ set equal to 20, 25, 30, 35.[2] As illustrated in the Figure the corresponding dates of transition T^* are equal to 8, 9, 10, 14 respectively. In terms of our model this implies complete adoption after 280, 315, 350, and 490 years respectively. Higher adoption costs are interpreted to be the result of institutional or structural features that have not been explicitly modeled here. However, the implication for cross country differences in income is obvious. Furthermore, another implication for countries facing high adoption

[2] In the empirical section of this paper we attempt a somewhat crude calibration exercise to fix an appropriate value of δ in a way that it matches the technology adoption pattern observed in a cross country data set. The appropriate value of this parameter is then approximately equal to 100. However, in our experiments in Section 3.1.1 we have reported results based on the assumption that δ is a free parameter. The qualitative insights that we are looking for are not sensitive to the range of values for δ considered in these experiments.

cost pertains to the level of inequality in the income distribution after the transition takes place. For example in Figure 4 we examine the Gini coefficients of capital and wealth over time for different adoption costs. It appears that the level of inequality of the post-transition capital and wealth distributions does not vary significantly as adoption costs increase.

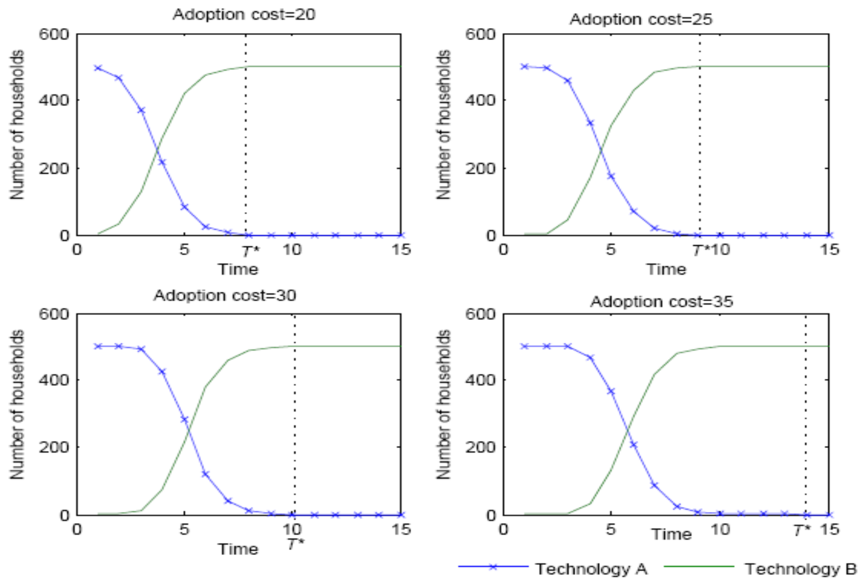

Figure 4 (a): Number of households adopting Technology A or B in different time periods with varying adoption costs.

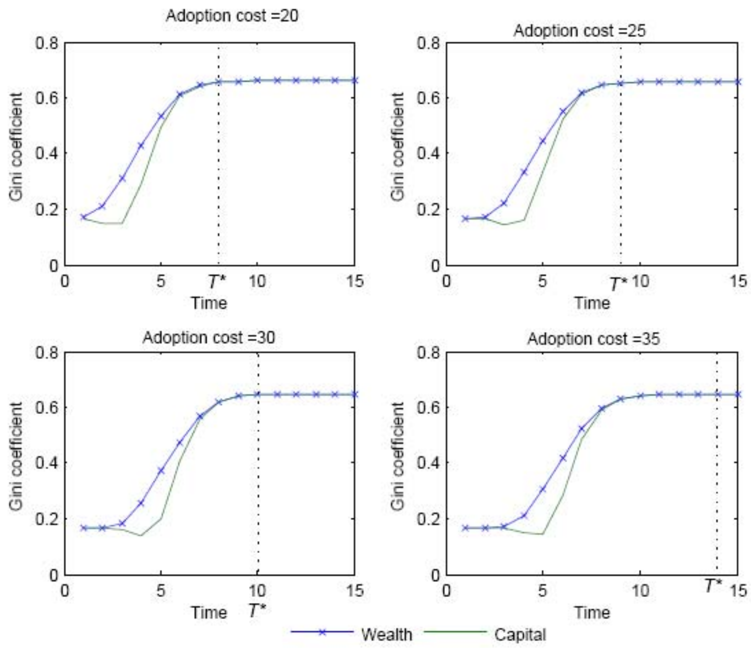

Figure 4 (b): Gini coefficients of capital and wealth over time for different adoption costs.

The results above motivate some simple thought experiments. That is, based on the impact of the magnitude of adoption costs on transition dates and inequality levels eventually attained, it is of interest to examine the effect of (a) adoption costs that vary *randomly* over time, and (b) adoption costs that *increase* over time. These experiments are further motivated by the idea that the growth experience of transitional economies in cross-country data exhibits a lot of diversity. Pritchett (1997) suggests that while some countries that fall in the category of "developing economies" have experienced rapid growth and convergence to higher income levels, others have experienced an interruption of the growth process manifested in the form of stagnation or even *reversals*.

In Figure 5(a) we examine the impact of adoption costs that vary randomly over time. We constructed the adoption cost series by using a uniform random number generator with a transformation that generated positive values of δ between 10 and 60. We find that although there are some reversals in the adoption process during the transition period, eventually complete adoption takes place. The variability of adoption costs appear to impact significantly on the date of eventual transformation. The experiment therefore indicates that varying adoption costs may be a potential candidate for explaining reversals in growth process that has been experienced by some developing economies. Note that we assume that there is no uncertainty associated with the household's technology adoption decision – the decision to adopt a particular technology is taken after the cost is observed by the household. An interesting extension of the model would entail considering a "risky" technology adoption decision whereby the costs are observed after the adoption decision takes place, and only the distribution of adoption costs is known.

In Figure 5(b) we look at increases in adoption costs over time. We consider experiments in which adoption costs grow at a rate of 10%, 15%, and 20% over time, starting at a minimum value of 20. Again, we emphasize that this is simply a thought experiment based on a somewhat "ad-hoc" process for adoption costs. Ideally, the variability in adoption costs should be modeled as a process that is *endogenous* in the sense that it arises due to some institutional or structural features characteristic of developing economies, and that is explicitly

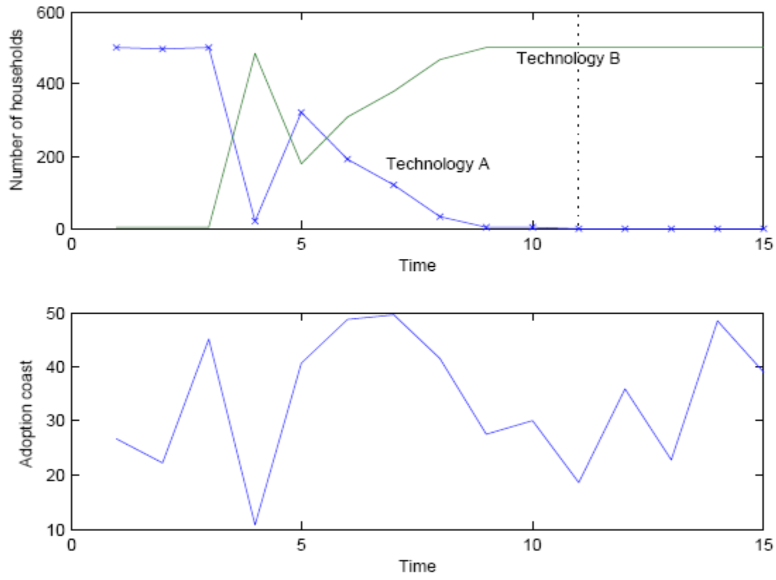

Figure 5(a): Impact of variability in adoption costs over time.

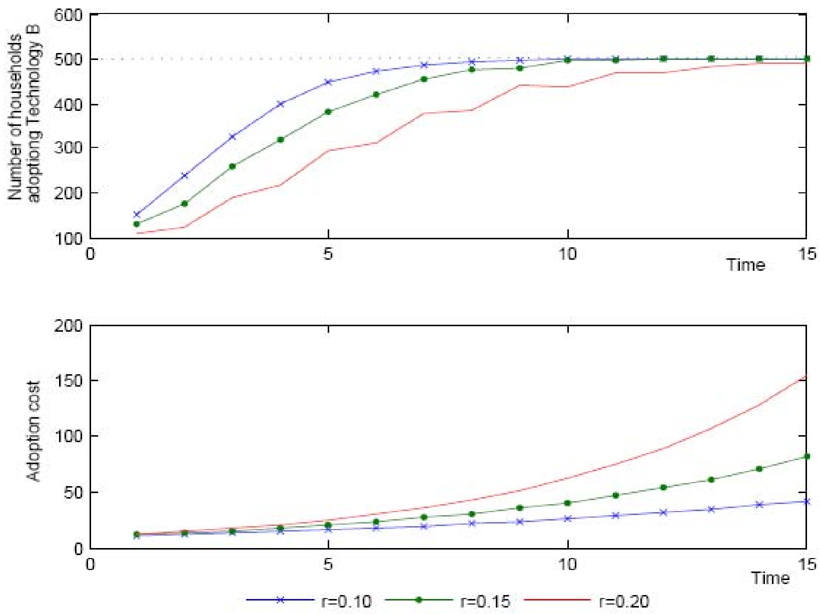

Figure 5(b): Impact of increases in adoption costs over time.

modeled into the framework. However, our purpose here is simply to explore whether this may be fruitful direction of research. To that end, the results reported in Figure 5(b) appear to support the idea that this may indeed be the case. Increasing adoption costs appear to significantly delay the process of complete adoption. For example corresponding to the adoption-cost growth rates mentioned above the transition to Technology B takes place approximately after 420, 455, and 525 years respectively.

3.1.2. Experiments that vary initial inequality levels

Next we consider the implications for varying levels of inequality in the initial distributions of wealth and capital, on the date of transition and eventual inequality levels. Figure 6 reports four panels which correspond to four different initial distributions that are essentially mean-preserving spreads of the distribution corresponding to Figure 1. That is the mean of all of the initial distributions is 3.5 with variances given by 1.01, 2.01, 2.80, 3.65 respectively. (The corresponding Gini coefficients of the initial distribution of wealth are: 0.1586, 0.2149, 0.2371, and 0.2741 respectively). In this figure we consider the impact on inequality levels in the post-transitional distributions of wealth and capital. Here, we find that higher levels of initial inequality translate into higher levels of post-transitional inequality. Also initial inequality levels impact on the date of complete adoption of the better technology. We also empirically test this result in section 4.2.

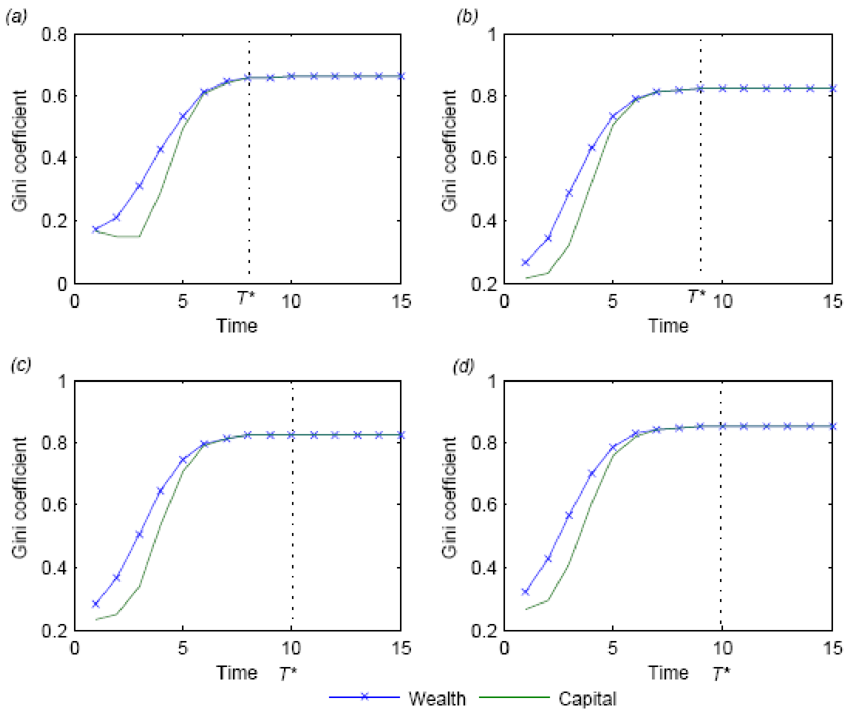

Figure 6: Gini coefficients of wealth and capital in different time periods with varying levels of initial inequality.

The results corresponding to Figures 6 have an interesting implication for future research. Since the process of transition has such stark distributional implications political economy issues cannot be ignored. It is for example, reasonable to argue that social and political conflict may ensue in the process of transition leading to an interruption of the process. This issue is addressed, for example, in Krusell and Rios-Rull (1996).

3.1.3. Growth patterns across different cohorts in the income distribution

Figure 7 examines the patterns in the evolution of output over time across different groups of household. This figure looks at the rate of growth of output for the median, richest 20% and poorest 20% of the households of the income distribution. (This experiment was also conducted for three other economic aggregates viz: wealth, savings and consumption).[3] The striking aspect here is that the growth pattern for different cohorts of households is very diverse. For example the timing of complete adoption and the timing of reversals and upswings in the growth process vary significantly across different groups. Furthermore, in some cases the pattern of growth is monotonic, while it is non-monotonic for others. One may in fact infer that this characteristic would also translate into a corresponding diversity in the experiences of *countries* that are in different positions in the *world* distribution of income. This feature of the model suggests that multi-country extension of this model similar in spirit to the framework considered in Basu and Weil (1998) with different income distributions across countries and a sequence of technologies with varying levels of productivity might yield a diversity of patterns that have been observed in the data.

[3] We do not present the results here, but they are available upon request.

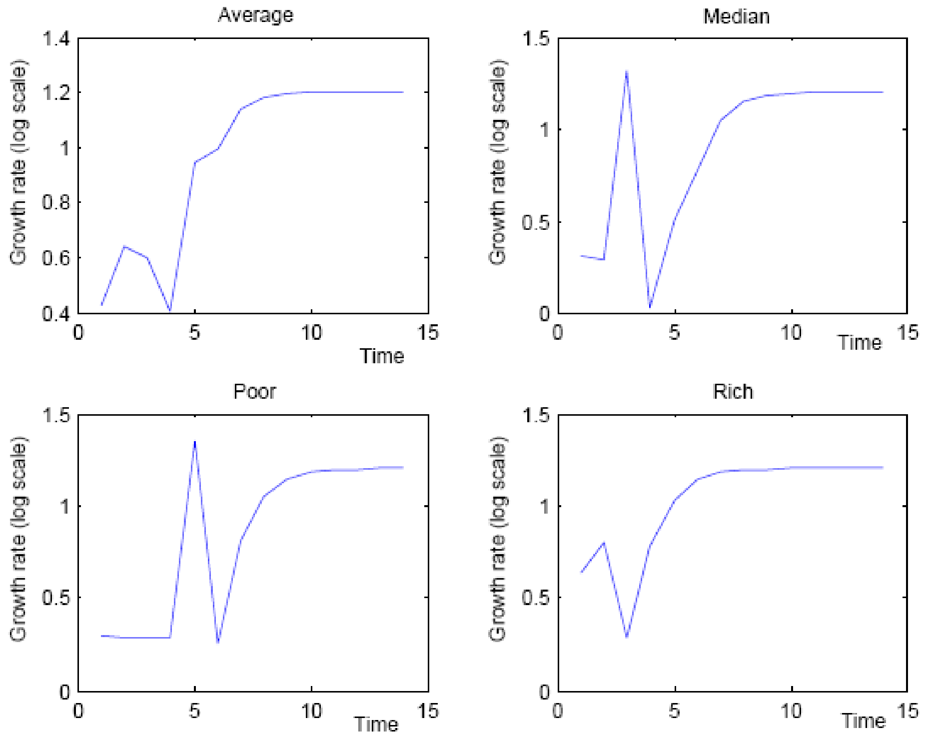

Figure 7: Growth rates experienced by the various cohorts of households

3.1.4. Experiments with θ

Consider Figures 8(a) and 8(b). The results of these experiments are briefly summarized as follows:

(i) Complete adoption to the more productive technology is faster for higher values of theta. This follows in part from the fact the threshold level of capital that facilitates adoption is decreasing in theta. When adoption costs are fixed, a more altruistic household is likely to adopt sooner as it enables the household to leave larger bequests for the next generation. Typically, prior to adoption of the more productive technology a household leaves a higher proportion of their income in the form of bequests. (See figure 8(b). In Figure 8(b) we present a transitional period in which all households have not yet adopted technology B for two cases: theta=1 and theta=1.5 Bequests as a proportion of income is higher in the case of theta = 1.5. Eventually after complete adoption the percentage of bequests left is constant, and lower in the case of theta =1 This feature of the model is consistent with empirical evidence. Based on panel data consisting of 659 estates in Ohio, U.S.A., Tomes (1981) finds that inheritance received from parents is inversely related to children's income.[4]

(ii) Post transitional inequality is lower for higher values of theta. Intuitively, quicker adoption to technology B reduces post-transitional inequality (See figure 8 (c)).

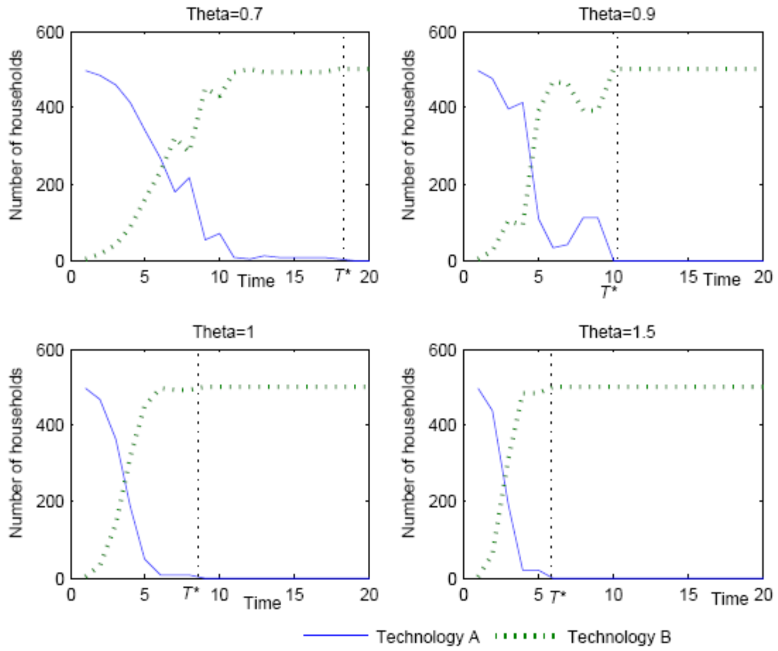

Figure 8 (a): Number of households adopting Technology A or B in different time periods with varying levels of altruism parameter (θ).

[4] Please see Owen and Weil (1997) and Borjas (1992) for further discussion.

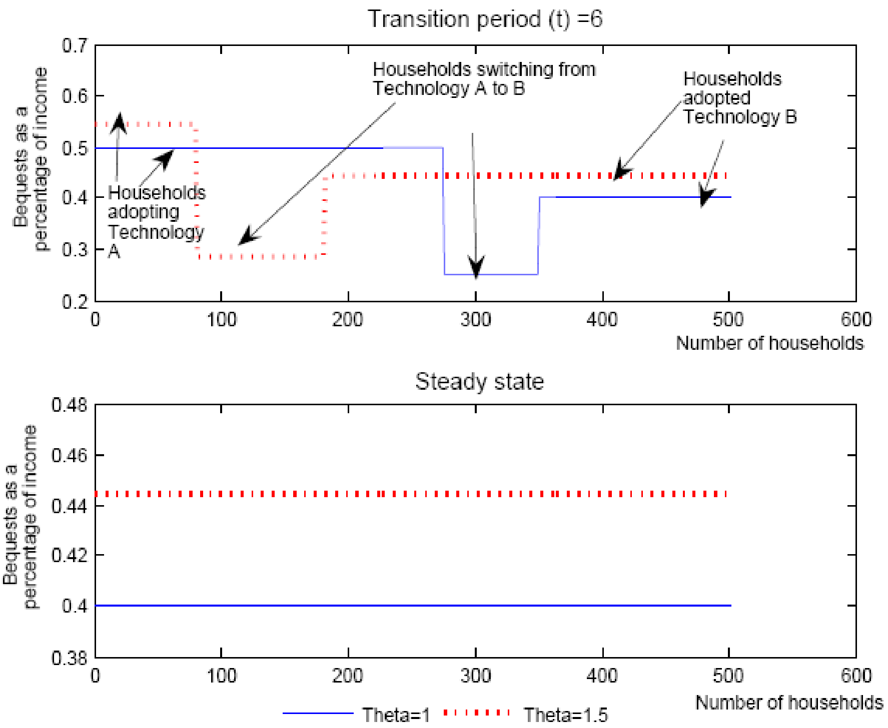

Figure 8 (b): Bequests as a proportion of income during transition and at steady state for different altruism parameter (θ).

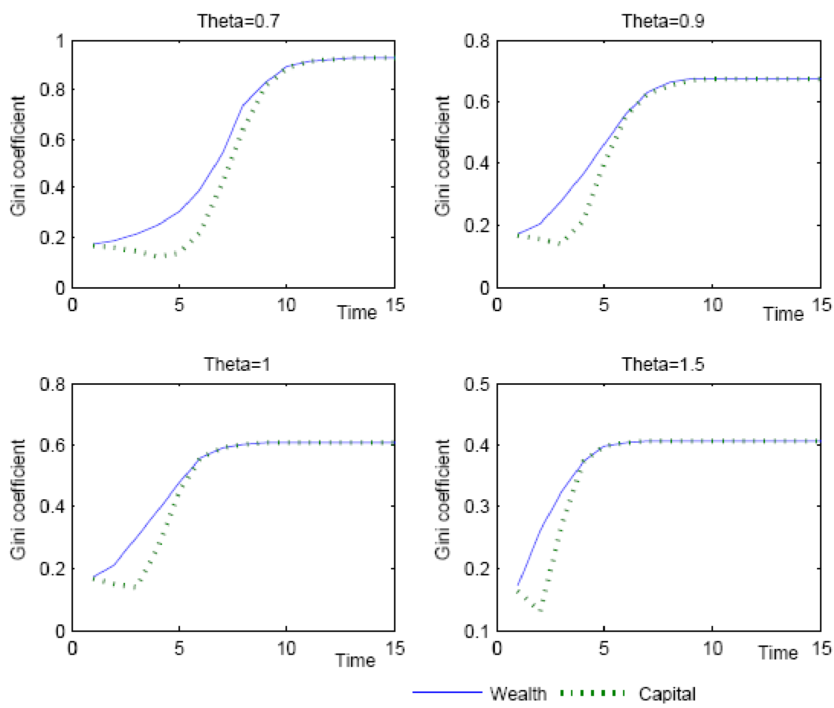

Figure 8 (c): Gini coefficients of capital and wealth over time for different altruism parameter (θ).

3.2. Household Specific Adoption Costs

We now consider the more general case of our model in which the adoption cost is a household specific stochastic shock, observed prior to the technology adoption decision. The values for the adoption cost parameter are drawn from shifted uniform distributions with varying means, keeping the variance constant.

3.2.1. Experiments with the adoption-cost parameter δ

Figure 9 reports the evolution of number of households adopting Technology A and B over time, for different *average* levels of the stochastic adoption cost parameter. Our results mostly follow the same interpretation in the special case of our model described previously. Unlike in the special case, one striking feature here, as illustrated by figure 9 is reversals and upswings in the adoption process. As a result, with household specific adoption cost, complete adoption of the better technology is impossible and the economy uses both technologies at any given time period. Furthermore this feature of the model suggests that the inequality in wealth and capital remains persistent.

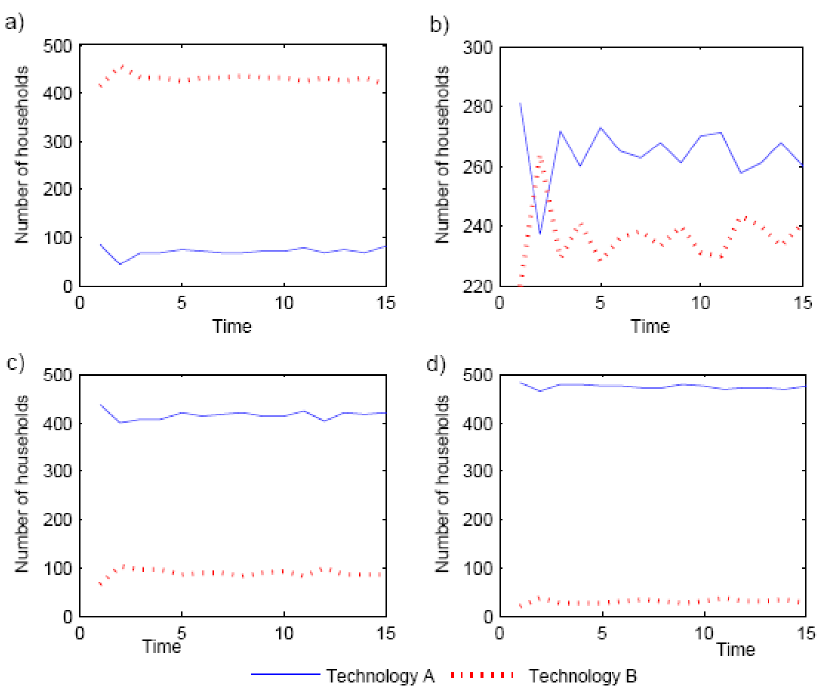

Figure 9: Number of households adopting Technology A or B in different time periods with varying adoption costs.

3.2.2. Experiments that vary initial inequality levels

Now we consider the implications for varying levels of inequality in the initial distributions of wealth and capital, on the date of transition and eventual inequality levels as we did in the special case our model. In this experiment also, we find reversals and upswings in the adoption process. According to our results, it appears that, even with and very low levels of initial inequality, complete adoption of the better technology never takes place and the inequality remain persistent. We do not present our results here, but they are available upon request.

3.2.3. Growth patterns across different cohorts in the income distribution

In our next experiment, we explore the pattern of growth rates in output, wealth, savings, and consumption in the economy with household specific adoption costs. Again our results exhibit diverse patterns of growth in these variables. Interestingly, in contrast to the model of the section 3.1.3, the more general model with household specific adoption costs is capable of producing negative growth rates during the transition process. (See figure 11). This illustrates the potential of our model in terms of its capability to capture the diversity of growth patterns across economies that we referred to earlier.

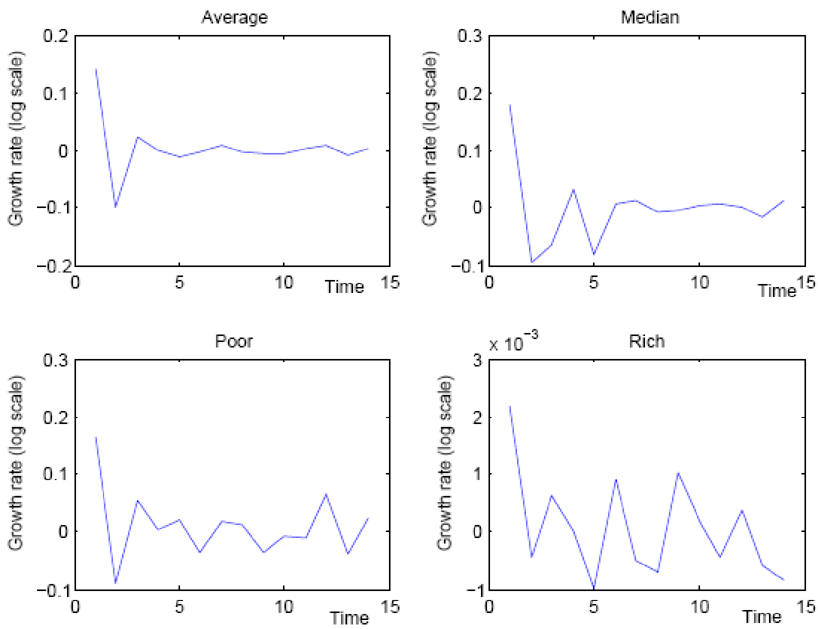

Figure 11: Rates of growth experienced by rich and poor cohorts of households.

3.2.4. Experiments with θ

In our last experiment, we examine the implications for the varying levels of altruism parameter with household specific stochastic shock in adoption costs, on the transition process of the economy. Our results do not differ significantly from the results we presented in section 3.2.1.[5] In this experiment also, it appears that, complete adoption to the better technology never takes place, even with more altruistic households in the economy. As a result, the inequality in the economy remains persistent.

4. Empirics

In this section we present some empirical findings that motivate and support some of the implications of the model of this paper. In section 4.1 we are interested in exploring the question: what value of the adoption cost parameter (δ) would lead to pattern of technology adoption that has been observed in a cross section of countries? In section 4.2 we use the same data set with additional variables to test the implication of our model that inequality impacts negatively on technology adoption.

4.1. Calibration of the adoption cost parameter

In order to answer the question relating to the adoption cost parameter (δ) we first construct an "Index of technology adoption" (ITA) for the model as well as the data.[6] This index, which may be considered a measure of the "extent of adoption" of a particular technology, is defined as follows.

$$ITA_i = \frac{N_i^B - N_{\min}^B}{N_{\max}^B - N_{\min}^B}$$

Where, N_i^B is the number of households in country *i* which have adopted a certain technology.

i=1,…,n.

$$N_{\min}^B = \min\left\{N_1^B, ...N_n^B\right\}$$

$$N_{\max}^B = \max\left\{N_1^B, ...N_n^B\right\}$$

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[5] Therefore we do not present our results here, but they are available upon request.
We use the "Technology: creation and diffusion" data base of Human Development Report (2006) and our data set consists of 104 countries.

We calculate this index for 3 different measures of what we refer to as Technology B. In the first case N_i^B, for example, represents the number of households per 1000 in country *i* that have adopted internet facilities. The other 2 proxy variables are (a) households per 1000 using telephones and (b) households per 1000 using cellular telephones. By averaging these 3 indices we construct a fourth index, which we refer to as an "aggregate index of technology adoption" (AITA). The variable in our model which is the counterpart to the adoption indices we have constructed, is simply given by,

$$ITA_t = \frac{N_t^B}{N}$$

Our interpretation of the subscript *t* is the "stage of development" so that it corresponds to the interpretation of the subscript *i* for the data set. In that sense, we are looking at a cross section of data that we interpret as countries at different stages of development as measured by the index of adoption. The model counterpart of the index however corresponds to "different time periods" which is also analogous to the idea of different stages of growth.

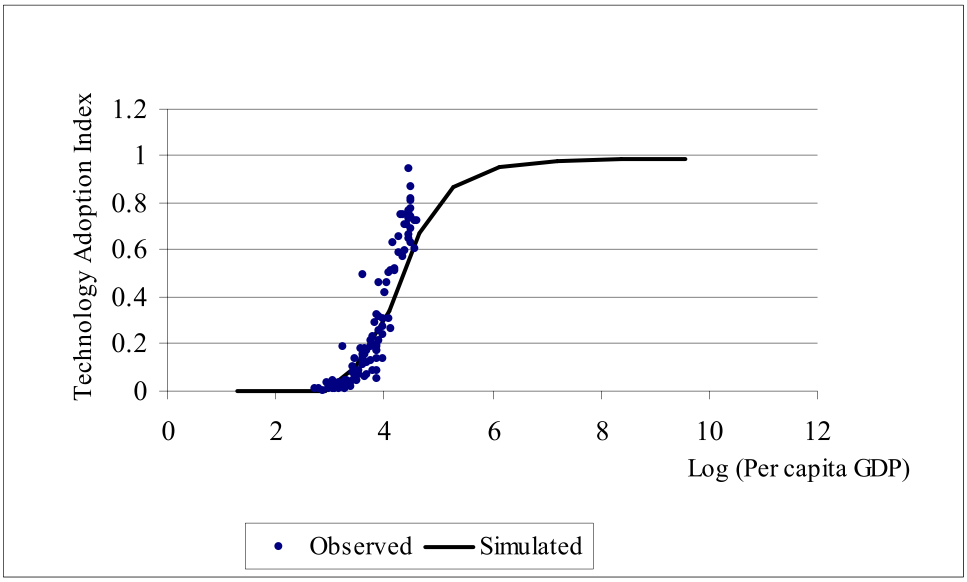

Figure 13: Technology adoption: model prediction and empirical observation.

In figure 13 we have log per capita GDP on the X axis and the technology adoption index on the Y axis. The technology adoption pattern in the model is represented by the solid line and in the data it is represented by the dotted line.[7] Our "inverse calibration" exercise tells us that a value of δ =100 provides a reasonable match with the data as illustrated in figure 13.[8] However while the model matches earlier stages of development relatively well, it is more pessimistic regarding "complete adoption" to better technologies.[9] Also while the model predicts a smooth transition towards complete adoption, the data is characterized by a discrete "jump" to "complete adoption".

4.2. Technology adoption and income inequality

In this part of our paper we present the results of an empirical examination that focuses on the model's implication of a negative link between income and wealth inequality within a country and the extent of technology adoption.

In order to test whether a country with more inequality in income and wealth distributions has a smaller extent to technology adoption, we further examine the technology adoption indicators that we estimated in the previous section. To that end, we examine a cross country data set for evidence of a negative correlation between degree of technology adoption and income and wealth inequality of a country. We measure the income and wealth inequality of a country by the Gini coefficient (X_1) and this is the main independent variable in our analysis.

We select other explanatory variables based on the following argument. The stylised facts of growth and development suggest that a primary factor determining the degree of technology adoption of any transitional economy is its level of output (Kuznets, 1955). Furthermore various institutional, structural, social and political characteristics may have implications for the adoption levels of various technologies. For example the levels of educational attainment of the population, longevity and health of the population, or the country's openness to trade with the rest of the world, may have implication

[7] We present our results using only the AITA measure, but we observe similar patterns in the case of other measures of technology adoption (i.e. ITA).

[8] As noted before, for the experiments conducted with the adoption costs parameter, results are not altered qualitatively when we consider magnitudes closer to this value.

[9] Note that the index of technology adoption we have constructed assigns the value of 1 to the country with the greatest extent of adoption, which is not really "complete adoption" in the sense implied by the model.

for the process of technology adoption. To that end, the set of other independent variables we include in our regression analysis are;

X_2=productivity level measured by GDP Index

X_3=level of human development measured by Human Development Index (HDI)

X_4=incentive measures of the federal government to promote technology adoption measured as a percentage of GDP on research and development.

X_5= degree of openness to trade with the rest of the world, measured as the ratio of imports over a country's GDP, following Caselli and Coleman (2001).

We therefore estimate a model of the form,

$$AITA_i = \alpha + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \beta_4 X_{i4} + \beta_5 X_{i5} + \varepsilon_i \qquad (14)$$

Where, $AITA_i$ is the aggregate index of technology adoption of country i, and X_{i1}…X_{i5} are the explanatory variables discussed above for i^{th} country. The error component is ε_i and it has usual properties $(\varepsilon_i \sim N(0,1))$. To check the robustness of our results we estimate equation 14 for 3 other measures of technology adoption discussed in the subsection 4.1, which we refer to as ITA-I, ITA-II, ITA-III respectively. For details of data set please see Appendix 1.

Table 2: Results of the estimated models

	AITA	ITA- I	ITA- II	ITA- III
α	-0.790	-.0623	-0.621	-0.989
X1	-0.002*	-0.004*	-0.004*	-0.003
	(0.099)	(0.047)	(0.014)	(0.154)
X2	1.061**	0.961*	0.909*	1.114**
	(0.000)	(0.019)	(0.021)	(0.003)
X3	0.182	0.399	0.679	-0.228
	(0.633)	(0.424)	(0.126)	(0.602)
X4	0.056**	0.020*	0.054**	-0.015*
	(.001)	(0.034)	(0.005)	(0.054)
X5	0.101*	0.011	-0.034	0.249**
	(0.068)	(0.902)	(0.592)	(0.002)
Adjusted R^2	0.879	0.683	0.845	0.786
Number of countries	105	126	126	116

We present our results in Table 2. The second column of the table represents the regression results for the model with degree of technology adoption measured in terms of the aggregate index of technology adoption (AITA). In the next 3 columns we show the regression results based on different measures of technology adoption discussed previously.

Our results appear to support the fact that there is a negative link between income inequality and country's degree of technology adoption. Further more the sign of coefficients of other variables are mostly consistent with the hypothesized impact on technology adoption except the openness variable in third regression and HDI variable and incentives for technology adoption variable in fourth regression.

5. Concluding remarks

Empirical evidence suggests that there has been a divergence over time in income distributions *across* countries and *within* countries. In this paper we study a simple dynamic general equilibrium model of technology adoption which is consistent with these stylized facts. In our model, growth is endogenous, and agents are assumed to be heterogeneous in their initial holdings of wealth and capital. In a special case of our model with fixed adoption cost across households, we find that in the presence of barriers or costs associated with the adoption of more productive technologies, inequalities in wealth and income may increase over time tending to delay the convergence in international income differences. The model also has the potential for explaining the observed diversity in the growth pattern of transitional economies. According to the model, this diversity may be the result of variability in adoption costs, or the relative position of a transitional economy in the world income distribution. In the more general case of the model with household specific adoption costs, negative growth rates during the transitional process are also possible. The results of our empirical study appear to support the model's prediction that inequality has negative impact on technology adoption.

Some of our quantitative experiments suggest some interesting directions for future research. Ideally, the variability in adoption costs should be modeled as a process that is *endogenous* in the sense that it arises due to some institutional or structural features characteristic of developing economies, and that is explicitly modeled into the framework. Furthermore, the inequalities that result from the process of transition indicate that political economy issues would also have a bearing on these issues. Risks associated with the variability of adoption costs may also be of importance.

Appendix 1 Data set

We use the "Technology: creation and diffusion" data base of the Human Development Report (2006). We use the data for 2004 from this source but, we exclude the countries with missing data from our analysis in each regression. As a result the number of countries included varies across the four models we estimate. In the case where Gini coefficient measure was not available for the year 2004, we used the nearest available estimate.

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