# Education Inequality among Women and Infant Mortality: A cross-country empirical investigation*

Chris Papageorgiou
Research Department
International Monetary Fund
Washington, DC 20431
E–mail: cpapageorgiou@imf.org

Petia Stoytcheva
Department of Economics and Finance
Salisbury University
Salisbury, MD 21801
E–mail: psstoytcheva@salisbury.edu

July 19, 2011

**Abstract**

We construct a cross-country dataset on female human capital inequality. Unlike the existing literature that primarily focuses on the average years of women's education, we use this dataset to examine the relationship between female human capital inequality and infant mortality. We show that higher education inequality among women, measured by the Gini coefficient, leads to substantially higher infant mortality. This finding is robust to various alternative specifications and subsamples considered. We also consider whether this channel is important in explaining growth. Growth regressions show favorable but weak evidence that education inequality among women is associated negatively with growth via its effect on infant mortality. Our main results have implications related to the policy question on the optimal allocation of educational subsidies. If infant mortality reduction is a priority for policy makers, then educating the least educated women first seems to be an effective (and also simple) policy recommendation.

**JEL Classification:** O10, O40.

**Keywords:** Women's education; education inequality; infant mortality; growth.

*We thank Oya Celasun, Areendam Chanda, Amporo Costelló, Doug McMillin, Robert Tamura, Marios Zachariadis, and participants in many universities and conferences this paper was presented. We are also grateful to Amporo Costelló and Rafael Domenech for making their dataset available to us. The views expressed in this study are the sole responsibility of the authors and should not be attributed to the International Monetary Fund, its Executive Board, or its management.

# 1 Introduction

It has been argued that lack of sufficient female education can be a major impediment to welfare and growth in developing countries. Improving female education is one of the most sought out Millennium Development Goals and one for which there have been many policy recommendations aiming for immediate and systematic progress. An important consequence of investing more in female education are the changes brought about in household behavior and practice. Advocates for increased female education have maintained that even a few years of education can empower women with skill necessary to increase their entire household productivity, to raise healthier children and to make better economic decisions. As suggested by Cutler, Deaton and Lleras-Muney (2006) "The importance of women's education is likely a result of the fact that as primary care takers, they are most likely to implement the health behaviors that can improve their children's health. To the extent that education improves an individual's ability to undertake these changes, more educated mothers will have healthier babies."

In 1971, only 22% of women, in contrast to 46% of men, were literate worldwide. Two decades later, 39% of women (and 64% of men) were literate. Thus, there has been a large increase in the proportion of women who are considered "literate" in the past 20 years. Despite these improvements, the large gap between the literacy levels of men and women continues to be substantial. There are dramatic differences in literacy rates by country, regions and by place of residence, with rates in rural areas lagging behind rates in urban areas. In 1991, the urban literacy rate was more than twice that of the rural rate, 64% and 31%, respective. Finally, literacy rates among women are shown to be particularly low in low-income and developing countries. For example, in 1991 less than 40% of the 330 million women (over the age of 7) were literate in India. Today this number has been drastically reduced to an estimated of 200 million – a magnitude that is still overwhelming.[1]

This paper offers three contributions to the literature that investigates the effect of female education on economic aggregates. First, unlike existing work that focuses primarily on the average years of female education, we construct a new cross-country dataset on female human capital *inequality*. Second, we use these new data to examine the relationship between female human capital inequality and infant mortality. Our hypothesis is that higher inequality in education among

[1]These data are taken from the U.S. Department of Commerce, Economics and Statistics Administration.

women may be partly responsible for higher infant mortality because mothers at the low end of the distribution lack the necessary skills to provide adequate care to their infants. Third, we empirically examine whether female education inequality affects growth via infant mortality. More specifically, we empirically test the following two-step relationship: In the first step, inequality in education among women leads to higher infant mortality. In the second step, we examine whether higher infant mortality is partly responsible for slow growth experienced by many developing countries.

Our female human capital inequality dataset is constructed following Castelló and Domenech (2002) who calculate Gini coefficients as a measure of human capital inequality, and Barro and Lee (2001) who provide data on male and female educational attainment. In particular, we construct female-specific education Gini coefficients for 108 countries and use this measure, in addition to average female education, to better capture the within-country distribution of women's education.[2] Focusing on the distribution rather than the mean of female education is important for our analysis; for example a developed country like the US may experience a relatively very high mean level of female education but with a large variance. Our Gini measure will be capturing the least educated women in the distribution allowing us to better measure the impact of female human capital education on infant mortality and subsequently growth.

There is a small, but rapidly growing macro literature explaining the decline in mortality over the last few decades (see Soares, 2007, for an excellent review). A more specialized set of papers suggest that women's education is a significant determinant of infant and child mortality. For example Schultz (1993) finds that at the sample mean, a one-year increase in women's education is associated with a 5% decline in child mortality. A related literature finds that mothers' schooling is considered to be an important determinant of the decline in infant and child mortality, presumably because they better manage child care by more effectively administering food and medical care. Technological progress is also considered to be one of the key reasons behind the mortality decline as argued by Jamison et al. (2001). In addition, Papageorgiou et al. (2007) using a novel dataset on medical imports show that medical technology diffusion is an important contributor to improved

[2]Due to the lack of available data on human capital inequality, little attention has been devoted to the influence of human capital distribution on economic growth in empirical studies. Birdsall and Londoño (1997) and López, Thomas and Wang (1998) are exceptions. The first study analyzes a sample of 43 countries and uses the standard deviation of years of education as the measure of human capital inequality. The second study uses a wider range of human capital inequality indicators but focuses on a reduced number of 12 Asian and Latin American countries.

health status, as measured by life expectancy and infant mortality rates.[3]

The rest of the paper is organized as follows. Section 2 takes a closer look at the data with special attention to the newly constructed female human capital inequality measure. Section 3 presents results from the empirical analysis, and examines robustness of the baseline results. Section 4 concludes.

# 2 A first look at the data

We start by describing the approach used to construct the measures of female (and male) human capital inequality. Next, we briefly discuss other variables used in the empirical analysis. Finally, we present descriptive statistics and density functions of the Gini coefficients of female, male and total (male and female) education. In addition, we present cross-sectional bivariate-correlations of the variables used in estimation.

## 2.1 Measuring female human capital inequality

The relevant new variable in our estimation is female human capital inequality. We follow Castelló and Domenech (2002) and construct the Gini coefficient of female (and male) human capital inequality for 108 countries, using the Barro and Lee (2001) dataset. We calculate the Gini coefficient as the mean of the difference between every possible pair of individuals divided by the mean size $\mu$,

$$G = \frac{\sum_{i=1}^{n}\sum_{j=1}^{n}|x_i - x_j|}{2n^2\mu}.$$

Since the Barro and Lee (2001) dataset provides information on the average years and attainment levels, the human capital coefficient ($G^h$) can be computed as follows:

$$G^h = \frac{1}{2\overline{H}}\sum_{i=0}^{3}\sum_{j=0}^{3}|\widehat{x_i} - \widehat{x_j}|\, n_i n_j, \tag{1}$$

[3]There is also substantial evidence from micro-development studies that supports female education having a substantial impact in lowering infant mortality. The vast majority of these papers use data at the micro level – village, province, or country level – that are considered more accessible and reliable (see e.g. Murthi, Guio and Drèze, 1995, Terra de Souza et al., 1999, and Dreze and Murthi, 2001). In addition, Breierova and Duflo (2002), taking advantage of a massive school construction program that took place in Indonesia between 1973 and 1978, show that female education is a stronger determinant of age at marriage and early fertility than male education. The literature that empirically investigates this relationship confirms a negative and statistically significant relationship between mother's education and child/infant mortality.

where $\overline{H}$ are the average schooling years of the population at age 15 and over, $i$ and $j$ are the different levels of education, $n_i$ and $n_j$ are the shares of population with a given level of education, and $\widehat{x_i}$ and $\widehat{x_j}$ are the cumulative average schooling years of each educational level. Castelló and Domenech (2002) consider the four levels of education used in Barro and Lee (2001): no schooling (denoted by 0), primary (denoted by 1), secondary (denoted by 2) and higher education (denoted by 3). Defining $x_i$ as the average schooling years of each educational level $i$, the cumulative average schooling years of each level can be written as

$$\widehat{x_0} \equiv x_0 = 0, \quad \widehat{x_1} \equiv x_1, \quad \widehat{x_2} \equiv x_1 + x_2, \quad \widehat{x_3} \equiv x_1 + x_2 + x_3 \tag{2}$$

Substituting equation (1) into equation (2), obtains[4]

$$G^h = n_0 + \frac{n_1 x_2 (n_2 + n_3) + n_3 x_3 (n_1 + n_2)}{n_1 x_1 + n_2 (x_1 + x_2) + n_3 (x_1 + x_2 + x_3)}. \tag{3}$$

The Barro and Lee dataset provides the estimates for two different age groups – age 15 and older, and age 25 and older – and a breakdown by sex at five-year intervals for the years $1960-2000$. This allows us to compute the Gini coefficient for the two genders. Since our sample is composed mainly from developing countries, we construct Gini coefficients for individuals over age 15. Using equations (2) and (3), the Gini Female education can be computed as

$$G^{fh} = n_0^f + \frac{n_1^f x_2^f (n_2^f + n_3^f) + n_3^f x_3^f (n_1^f + n_2^f)}{n_1^f x_1^f + n_2^f (x_1^f + x_2^f) + n_3^f (x_1^f + x_2^f + x_3^f)}, \tag{4}$$

where $n_0 = luf15$, $n_1 = lpf15, n_2 = lsf15$, $n_3 = lhf15$, $\overline{H} = tyrf15$, $x_0 = 0$, $x_1 = pyrf15/(lpf15 + lsf15 + lhf15)$, $x_2 = syrf15/(lsf15 + lhf15)$ and $x_3 = hyrf15/lh15$.Follow the Barro-Lee dataset, $luf$ is the percentage of "no schooling" in the female population; $lpf$ is the percentage of "primary school attained" in the female population; $lsf$ is the percentage of "secondary school attained" in female population; $lhf$ is the percentage of "higher school attained" in female population; $tyrf$ is the average schooling years in the female population; $pyrf$ is the average years of primary schooling in the female population; $syrf$ is the average years of secondary schooling in the female population; $hyrf$ is the average years of higher schooling in the female population.[5]

[4]For more details, refer to Castelló and Domenech (2001, pp. C189-C190).

[5]Similarly, Gini Male can be computed in the following way:

Table 1: Regional descriptive statistics

| Geographic Regions | Gini | Mean | Stand. Dev. | Min. | Max. |
|---|---|---|---|---|---|
| East, South Asia & Pacific | Gini Female | 0.533 | 0.252 | 0.161 | 0.961 |
| | Gini Male | 0.432 | 0.206 | 0.179 | 0.808 |
| Europe | Gini Female | 0.268 | 0.113 | 0.146 | 0.620 |
| | Gini Male | 0.251 | 0.077 | 0.136 | 0.441 |
| Latin America & Caribbean | Gini Female | 0.410 | 0.151 | 0.219 | 0.818 |
| | Gini Male | 0.380 | 0.123 | 0.198 | 0.651 |
| Middle East & North Africa | Gini Female | 0.661 | 0.148 | 0.295 | 0.798 |
| | Gini Male | 0.540 | 0.128 | 0.257 | 0.690 |
| North America | Gini Female | 0.256 | 0.042 | 0.226 | 0.286 |
| | Gini Male | 0.286 | 0.026 | 0.268 | 0.305 |
| Sub-Saharan Africa | Gini Female | 0.683 | 0.182 | 0.278 | 0.941 |
| | Gini Male | 0.576 | 0.156 | 0.290 | 0.877 |
| **World** | **Gini Female** | **0.507** | **0.238** | **0.146** | **0.961** |
| | **Gini Male** | **0.431** | **0.187** | **0.136** | **0.877** |

Notes: The mean, the standard deviation, the minimum and the maximum values presented above are computed for 19 countries in East, South Asia&Pacific, 22 countries in Europe, 23 countries in Latin America&Caribbean, 9 countries in Middle East&North Africa, 2 countries in North America, 29 countries in sub-Saharan Africa - see Appendix B for countries in geographic regions.

Next, we present descriptive statistics of the Gini coefficients for Female and Male education. Table 1 presents the mean, the standard deviation and the minimum and maximum of the two measures on human capital inequality for six geographic regions and the world for the period 1960-2000.[6]

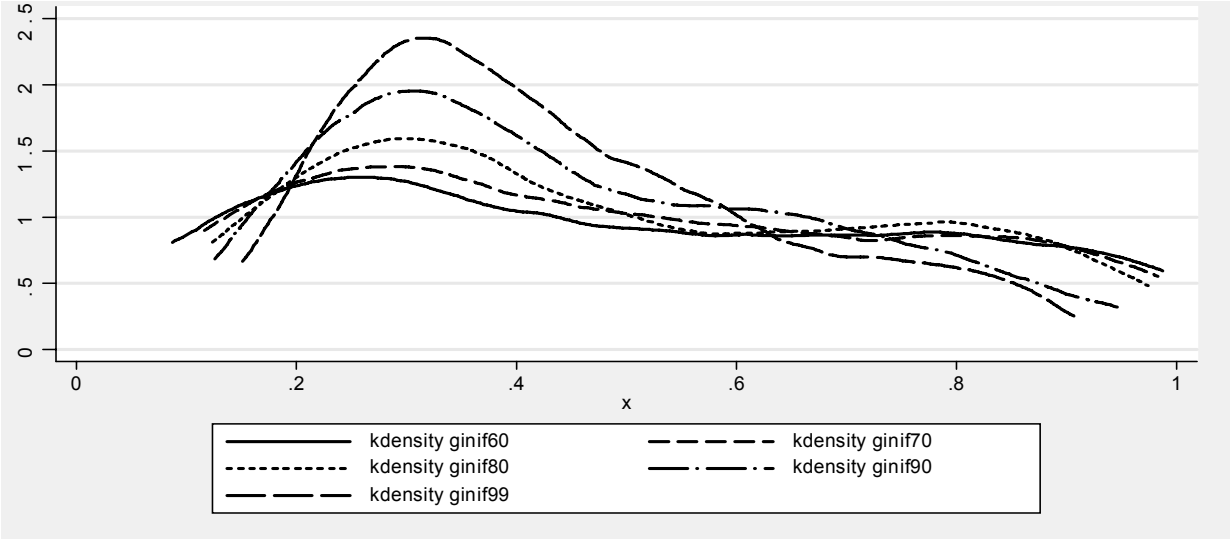
A number of points are worth noting here. First, the two regions with the highest female and male human capital inequality are the Middle East & North Africa and sub-Sahara Africa. In particular, the Gini Female education is the highest in sub-Saharan Africa, 0.683, while the Gini Male is 0.576. This coincides with the region's worst rates of infectious diseases including AIDS and malaria and also having the highest rates of infant mortality. Europe and North America experience the lowest human capital inequality. Finally, Latin America & Caribbean experience

$$G^{mh} = n_0^m + \frac{n_1^m x_2^m (n_2^m + n_3^m) + n_3^m x_3^m (n_1^m + n_2^m)}{n_1^m x_1^m + n_2^m (x_1^m + x_2^m) + n_3^m (x_1^m + x_2^m + x_3^m)}, \tag{5}$$

where $n_0 = lum15$, $n_1 = lpm15, n_2 = lsm15$, $n_3 = lhm15$, $\overline{H} = tyrm15$, $x_0 = 0$, $x_1 = pyrm15/(lpm15 + lsm15 + lhm15)$, $x_2 = syrm15/(lsm15 + lhm15)$ and $x_3 = hyrm15/lhm15$.

[6]The regional classification is taken from the WDI (2002).

Figure 1: Density functions for Gini Female (1960-2000)




considerably higher female and male human capital inequality than Europe and North America. The large standard deviation of the Gini Female indicates that there exists substantial variation among countries in these regions.

Figure 1 presents the distribution of female human capital inequality for 1960, 1970, 1980, 1990 and 1999. These distributions are constructed by non-parametric estimation of the density functions of the Gini using a truncated gaussian kernel for a distribution in the interval $[0, 1]$. It is shown that the density concentrates around a Gini Female coefficient of 0.3 which implies a quite uneven distribution of human capital among women. Also interesting is the dynamic evolution of these distributions. It is clear that from 1960 to 1999 there is systematic flattening of the distribution indicating a more equal distribution of women's education. However, what Figure 1 also shows is that although inequality in education among women has been decreasing over time, it still remains at very high levels.

## 2.2 Other variables

Our empirical analysis is based on two equations: one, where the dependent variable is infant mortality rate,[7] averaged for the period 1960-2000 (data is taken from the World Development

[7]Infant mortality rate is the number of infants dying before reaching one year of age per 1,000 live births in a given year.

Indicators, 2002), and a second growth equation that is derived from augmenting the Solow growth model. For the baseline estimation of our first equation, we include in addition to the female Gini coefficient, the number of physicians per $1,000$ people (WDI) and malaria in 1966, which is the percentage of country area with malaria (Gallup and Sachs, 2001) as control variables. We also include a measure of the mean level of female human capital defined as the average schooling years in the female population (Barro and Lee, 2001), over 15 years of age, averaged over 1960-2000.[8]

Due to constraints with the human capital data, our sample size is reduced to 73 countries. Data on real gross domestic product (RGDP) per capita are from the PWT version 6.1. We average the population growth of the working-age population $n$ for the period 1960-2000 and add $g + \delta$, which is assumed to be 0.05. The saving rate $s_k$ is the ratio of average investment to GDP over the 1960-2000 period (PWT 6.1) and $s_h$ measures the percentage of the working-age population that is in secondary school (Barro and Lee, 2001). For our panel regressions, we average the data into five-year non-overlapping time intervals. For the growth regressions we include initial GDP; this is GDP per worker in 1960 in the cross-sectional analysis and GDP per worker at the beginning of each five-years period in the panel estimation.

In examining the robustness of our baseline results we also consider a set of additional control variables. More specifically, in the robustness analysis of our first equation we considered Gini Male, Tropics, Latitude, Gini Income and Public Health Expenditure. In the robustness of our second (growth) equation we considered Government Expenditure, and three regional dummies (Latin America, Asia, Africa).

### 2.3 Bivariate correlations

Table 2 presents cross-sectional bivariate correlations between the variables used in estimation. The correlation between $GiniF$ and $infant$ is very high at 0.86 (Figure 2 presents a scatter plot of the correlation). However notice that also $GiniM$ is highly correlated with $infant$ (0.81). Whether male human capital inequality matters for infant mortality is an interesting question and we will address it later on. The correlation coefficient between $infant$ and $Growth$ is $-0.46$.There is also a strong negative correlation between $phys$ (the number of physicians per 1,000 people) and $infant$ ($-0.81$). Countries that are located near to the tropics also tend to have higher infant

[8]Summary statistics of the relevant variables are presented in Table A1, Appendix A.

Table 2: Cross-sectional bivariate correlations

| | infant | Growth | GiniF | schoolf | phys. | malaria | $(Y/L)_{60}$ | inv. | pop. | hum. |
|---|---|---|---|---|---|---|---|---|---|---|
| infant | 1 | | | | | | | | | |
| Growth | -0.46 | 1 | | | | | | | | |
| GiniF | 0.86 | -0.39 | 1 | | | | | | | |
| schoolf | -0.84 | 0.30 | -0.76 | 1 | | | | | | |
| phys. | -0.81 | 0.35 | -0.68 | 0.28 | 1 | | | | | |
| malaria | 0.79 | -0.25 | 0.66 | -0.24 | -0.75 | 1 | | | | |
| $(Y/L)_{60}$ | -0.84 | 0.16 | -0.75 | 0.26 | 0.81 | -0.77 | 1 | | | |
| inv. | -0.74 | 0.48 | -0.68 | 0.38 | 0.62 | -0.60 | 0.56 | 1 | | |
| pop. | 0.72 | -0.41 | 0.63 | -0.23 | -0.76 | 0.65 | -0.67 | -0.53 | 1 | |
| hum. | -0.84 | 0.47 | -0.87 | 0.55 | 0.69 | -0.69 | 0.73 | 0.72 | -0.51 | 1 |

Notes: The sample size is 73 countries. $GiniF$ is the average Gini for female education, $GiniM$ is the average Gini for male education, $schoolf$ is mean years of female education over the age of 15, $phys.$ is number of physicians per 1000 people, $malaria$ is the percentage of country area with malaria, $Y/L_{60}$ is initial GDP, $inv.$ is the ration of Investment to GDP, $pop.$ is average population growth, and $hum.$ is the percentage of the working-age population that is in secondary school.

mortality (correlation is 0.62) The correlation coefficient between $malaria$ and $infant$ is high and positive (0.79). Finally, the correlation between growth rate of GDP per worker and initial income, population growth, schooling and infant mortality is $0.16, -0.41, 0.47$, and $-0.46$, respectively.

# 3 Empirical Estimates

## 3.1 Inequality in female education and infant mortality

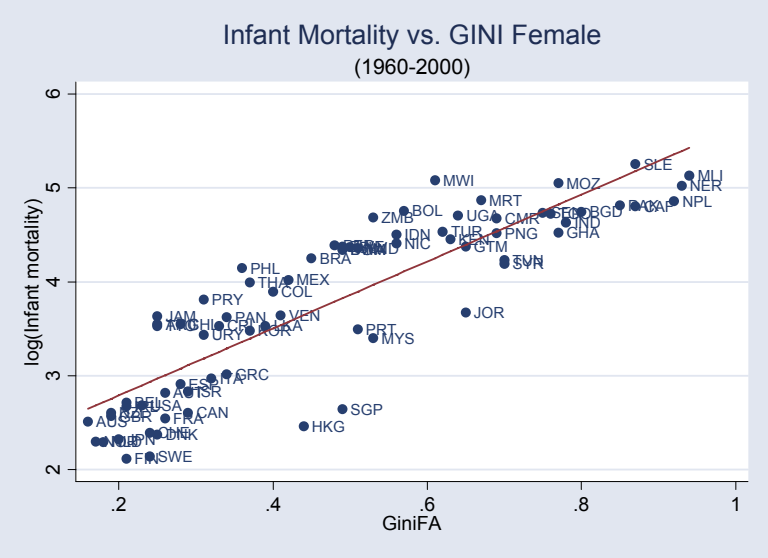
We start by testing the hypothesis that female education inequality is associated with infant mortality. Our benchmark estimable equation is:

$$\ln(infant)_i = \alpha_0 + \alpha_1 GiniF_i + \alpha_2 Growth + \alpha_3 \ln(phys)_i + \alpha_4 \ln(schoolf)_i + \alpha_5 malaria_i + \varepsilon_i. \tag{6}$$

Table 3 presents our baseline results.[9] Since our variable of interest is $GiniF_i$, in specification (1) we estimate the equation with only a constant, $GiniF$ and $Growth$. We obtain a positive and

[9]We average the right-hand side variables since the classical (white noise) measurement error gets averaged away at least partially. Hauk and Wacziarg (2004), using Monte Carlo simulations, show that averaging the right-hand side variables is very effective in reducing biases attributable to measurement error. Similarly, the same authors argue that averaging variables over time drastically reduces the incidence of measurement error compared to the case where they are entered at their values for any given year.

Figure 2: Scatter plot of infant mortality vs. Gini Female




significant estimate at the 1% level showing that higher female human capital inequality leads to higher infant mortality. We obtain a negative and highly significant coefficient estimate at the 5% estimate for *Growth*, indicating that higher growth of GDP leads to lower infant mortality.

In specification (2) we add *phys* Our results show that an increase of 1 physician per $1,000$ individuals leads to a reduction in infant mortality of 0.32 percentage points. The estimate on $GiniF$ is positive and significant, and the coefficient on *Growth* remains negative and significant.

In specification (3) we add $schoolf$,which is the average schooling years in the female population (Barro and Lee, 2001). The estimate on $schoolf$ is negative, but not significant. The estimate on $GiniF$ continues to be positive and highly significant, but decreases its magnitude to 1.5935. This implies that a 0.1 unit increase in $GiniF$ leads to 1.594 percentage change in infant mortality. The estimate on *Growth* is negative, but not significant, and the estimate on *phys* stays significant, negative and almost identical in terms of the magnitude. In specification (4) we exclude $GiniF$ but retain $schoolf$. We notice that the estimate on $schoolf$ is negative and significant at the 1% level, confirming the negative relationship between infant mortality and female education. More importantly, however, it shows that by omitting to also include $GiniF$ we miss the distributional effects of female education on infant mortality and misguidedly attribute this negative effect on the mean level rather than the disparity of female education. In specification (5)−representing

Table 3: Infant mortality regressions: Baseline results

| Dependent variable: ln(Infant) | | | | | | | |
|---|---|---|---|---|---|---|---|
| Specification | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| Estimation | OLS | OLS | OLS | OLS | OLS | Panel-BE | Panel-TE |
| Constant | 2.3616*** | 3.1778*** | 3.7049*** | 4.9329*** | 3.2547*** | 3.1421*** | 3.5689*** |
| | (0.1665) | (0.1818) | (0.4684) | (0.0935) | (0.4393) | (0.4864) | (0.2326) |
| GiniF | 3.3356*** | 2.2472*** | 1.5935*** | - | 1.5965*** | 1.5415** | 1.3296*** |
| | (0.2271) | (0.2490) | (0.6046) | - | (0.5712) | (0.6345) | (0.2986) |
| Growth | −0.2419** | −0.2035** | −0.1679 | −0.1264 | −0.2280** | −1.2625* | −0.5482*** |
| | (0.1067) | (0.1005) | (0.1049) | (0.1051) | (0.1097) | (0.6984) | (0.1842) |
| ln(phys) | | −0.3239*** | −0.3231*** | −0.3763*** | −0.1966** | −0.0898 | −0.0646** |
| | | (0.0686) | (0.0669) | (0.0721) | (0.0720) | (0.0594) | (0.0270) |
| ln(schoolf) | | | −0.1939 | −0.5508*** | −0.1011 | −0.2117 | −0.2280*** |
| | | | (0.1741) | (0.0915) | (0.1511) | (0.1632) | (0.0837) |
| malaria | | | | | 0.5397*** | 0.6925*** | 0.8389*** |
| | | | | | (0.1499) | (0.1590) | (0.0684) |
| *Adj.* $R^2$ | 0.76 | 0.83 | 0.83 | 0.81 | 0.85 | 0.81 | 0.77 |
| Obs. | 73 | 73 | 73 | 73 | 72 | 396 | 396 |

Notes: Standard errors are in parentheses. White's heteroskedasticity correction was used. *** Significantly different from 0 at the 1% level. ** Significantly different from 0 at the 5% level. * Significantly different from 0 at the 10% level.

our benchmark estimable equation (6), we add *malaria*. As expected we obtain a positive and significant estimate on *malaria*, suggesting that an increase in a country's area with malaria by 1% leads to an increase in infant mortality by 0.5397 percentage points. We notice that the estimate on $GiniF$ continues to be positive and highly significant, while the estimate on $schoolf$ is insignificant.

Next, we extend our baseline cross-sectional estimation to panel estimation. An advantage of using panel data is that we can control for unobserved heterogeneity across countries by taking into account the additional information in the time dimension of the data.[10] Following much of the

[10]Temple (1999) discusses several advantages of using panel data analysis. First, it allows one to control for omitted variables that are persistent over time. For example, variations in technology across countries are likely to be correlated with the regressors. By using the panel data technique, the unobserved heterogeneity in the initial level of efficiency is controlled for. Second, it allows several lags of the regressors to be used as instruments. A commonly used approach in the literature is GMM to estimate dynamic panel data models. Despite these advantages, panel data techniques leave some uncertainty about the time intervals. Most researchers find it useful to use five or ten year averages to avoid business cycle effects.

literature on cross-country panel estimation, we average the data in five-year time intervals. Our resulting panel is unbalanced with a total of 396 observations with a maximum of 8 observations for each of the 73 countries considered.

In specification (7) of Table 3 we estimate the model using the Between Estimator.[11] In a recent paper Hauk and Wacziarg (2004) argue that using an OLS estimator applied to a single cross-section of variables averaged over time (BE) performs best in terms of the extent of bias on each of the estimated coefficients. Using this estimator we find that the estimate on $GiniF$ is positive and significant at the 5% level, the estimate on $Growth$ is negative and significant at the 10% level, the coefficient on $malaria$ is significant at the 1% level, whereas the estimate on $schoolf$ is insignificant as is the coefficient on $phys$. To allow for the possibility of time effects, specification (8) includes $(T-1)$ time dummies meant to capture exogenous shocks specific to each five-year period. The coefficient of $GiniF$ continues to be positive and highly significant, and that of $Growth$ and $phys$ are negative and significant. Finally, the estimate on $malaria$ is positive and highly significant.[12]

To summarize, our key estimate on female human capital inequality is found to be significant in the different specifications considered. Even when it is included aside $schoolf$, it continues to be positive and highly significant. This confirms our main hypothesis that higher inequality in education among women is a key determinant for higher infant mortality.

### 3.2 Robustness analysis

We begin the robustness analysis by including $GiniF$ *and* $GiniM$ in the baseline regression. Table 4 column (1) shows that the estimate on $GiniF$ is significant at the 1% level, while the estimate on $GiniM$ is insignificant.

We further explore the robustness of our results to the inclusion of other relevant variables motivated by theory and commonly used in the existing literature. In column (2) of Table 4 we

[11] See Greene (2000, Ch.14, pp. 562-565) for further information on the Between Estimator.

[12] Furthermore, to account for the possibility of country-specific effects as well as time effects, we estimate a two-way fixed-effect specification that involves the addition of 73 country-specific dummy variables and 7 time dummy variables. However, as there are more coefficients to estimate, we lose a large number of degrees of freedom which clearly biases our estimates resulting in nonsensical results. As Griliches and Hausman (1986) note, in regressions using panel data with fixed effects specifications, measurement error in the explanatory variables can lead to coefficient estimates that are "too low" and therefore insignificant; in controlling for the various fixed effects, the relative importance of measurement errors in the explanatory variables becomes greatly exacerbated, biasing coefficient estimates.

Table 4: Infant mortality regressions: Robustness results

| Dependent variable: ln(Infant) | | | | | |
|---|---|---|---|---|---|
| Specification | (1) | (2) | (3) | (4) | (5) |
| Estimation | OLS | OLS | OLS | OLS | OLS |
| Constant | 2.9856*** | 2.5254*** | 3.1822*** | 3.1936*** | 3.5089*** |
| | (0.4384) | (0.5835) | (0.5541) | (0.4369) | (0.4548) |
| GiniF | 1.1806* | 1.6504** | 1.6408** | 1.8409*** | 1.4327*** |
| | (0.7148) | (0.7288) | (0.6407) | (0.5866) | (0.5726) |
| Growth | −0.2117** | −0.2105* | −0.2097 | −0.1332 | −0.2428** |
| | (0.1050) | (0.1139) | (0.1335) | (0.1078) | (0.1090) |
| ln(phys) | −0.2112*** | −0.1595* | −0.1756** | −0.1345** | −0.2070*** |
| | (0.0733) | (0.0820) | (0.0798) | (0.0663) | (0.0706) |
| ln(schoolf) | −0.0290 | −0.1650 | −0.1081 | −0.1275 | −0.1255 |
| | (0.1483) | (0.2027) | (0.1441) | (0.1468) | (0.1511) |
| malaria | 0.5384*** | 0.3929** | 0.5004** | 0.4094** | 0.5104*** |
| | (0.1504) | (0.1783) | (0.2028) | (0.1655) | (0.1401) |
| GiniM | 0.9162 | | | | |
| | (0.6174) | | | | |
| GiniY | | 0.0188*** | | | |
| | | (0.0051) | | | |
| tropics | | | 0.0789 | | |
| | | | (0.2157) | | |
| latitude | | | | −0.0060*** | |
| | | | | (0.0020) | |
| public | | | | | −3.3793* |
| | | | | | (1.9990) |
| *Adj.* $R^2$ | 0.86 | 0.88 | 0.85 | 0.87 | 0.86 |
| Obs. | 72 | 59 | 72 | 72 | 72 |

Notes: Standard errors are in parentheses. White's heteroskedasticity correction was used. *** Significantly different from 0 at the 1% level. ** Significantly different from 0 at the 5% level. * Significantly different from 0 at the 10% level.

use Deininger and Squire (1996) measure of income inequality ($GiniY$) averaged over our relevant period. Data constraints with the Deininger-Squire dataset reduces our sample size to 59 countries. We notice that the $GiniY$ coefficient is positive and highly significant, but also the estimate on $GiniF$ continues to be positive and highly significant. We also consider tropics and latitude as additional regressors (columns 3 and 4 in Table 4, respectively). *tropics* controls for regions with tropical climate, such as sub-Saharan Africa. This variable takes a value of 1 if a country's entire land area is subject to a tropical climate, and 0 for a country with no land area subject to tropical climate. *latitude* is measured as the distance from the equator and proxies for how temperate a country is. Our main results with regards to estimated coefficient of $GiniF$ are robust to these variables.

In summary, the baseline results presented in Table 3 are in general quite robust to the inclusion of additional covariates as shown in Table 4.[13] The estimate on $GiniF$ is positive and significant in the different specifications, confirming the positive relationship between female human capital inequality and infant mortality.

### 3.3 Effects on Growth

Next, we consider the potential effect of female education inequality on growth via infant mortality. Specifically, we consider the following growth regression equation consistent with the estimation equation in Domenech and Castelló (2002):[14]

$$\begin{aligned}\ln(Y/L)_{i,2000} - \ln(Y/L)_{i,1960} &= \beta_0 + \beta_1 \ln(Y/L)_{i,1960} + \beta_2 \ln(s_{ik}) + \beta_3 \ln(n_i + g + \delta)_i + \beta_4 \ln(s_{ih}) \\ &\quad + \beta_5 \ln(infant)_i + \beta_5 \mathbf{X}_i + \varepsilon_i, \end{aligned} \tag{7}$$

where our dependent variable is growth of GDP per working age person, averaged over 1960-2000, $s_k$ is the ratio of average investment to GDP, $s_h$ is secondary school enrollment of working-age population, $n$ is average population growth, $g + \delta = 0.05$ as in Mankiw, Romer and Weil (1992), $infant$ is infant mortality, $\mathbf{X}$ is a set of other covariates including government expenditure ($gov$) and female education inequality ($GiniF$), and $\varepsilon$ is an error term.

Table 5 presents the results from our estimation. In specification (1) we estimate the standard Solow growth model with human capital, investment, population growth and initial income. The

[13] To save space we do not report results with various other control variables considered because our key results are qualitatively unaffected.

[14] This equation is also consistent with the estimation equation in Domenech and Castelló (2002).

Table 5: Cross-country growth regressions

| Dependent variable: $ln(Y/L)_{i,2000} - \ln(Y/L)_{i,1960}$ | | | | | |
|---|---|---|---|---|---|
| Specification | (1) | (2) | (3) | (4) | (5) |
| Estimation | OLS | OLS | OLS | OLS | 2SLS |
| Constant | 3.6035*** | 6.1072*** | 6.4300*** | 5.5240*** | 6.0687*** |
| | (0.6785) | (1.5477) | (1.4916) | (1.5186) | (2.1356) |
| $\ln(Y/L)_{1960}$ | −0.4837*** | −0.5976*** | −0.5968*** | −0.5635*** | −0.5883*** |
| | (0.0963) | (0.1267) | (0.1233) | (0.1258) | (0.1378) |
| $\ln(s_k)$ | 0.1869 | 0.0979 | 0.0474 | 0.0395 | 0.0181 |
| | (0.1737) | (0.1769) | (0.1957) | (0.1870) | (0.2245) |
| $\ln(n+g+\delta)$ | −0.3211*** | −0.2404*** | −0.1914** | −0.2277** | −0.2097** |
| | (0.0661) | (0.0883) | (0.0892) | (0.0915) | (0.0983) |
| $\ln(s_h)$ | 0.5203*** | 0.3708*** | 0.3768*** | 0.6011*** | 0.5746*** |
| | (0.0835) | (0.1173) | (0.1206) | (0.1896) | (0.1789) |
| ln(infant) | | −0.3109* | −0.3257* | −0.3591** | −0.4311* |
| | | (0.1831) | (0.1722) | (0.1672) | (0.2472) |
| ln(gov) | | | −0.0099 | −0.0110 | −0.0112 |
| | | | (0.0077) | (0.0077) | (0.0080) |
| GiniF | | | | 1.0568 | 1.0914 |
| | | | | (0.6751) | (0.7032) |
| $\chi^2$ *Sargan* | | | | | [0.4430] |
| $Adj.R^2$ | 0.45 | 0.47 | 0.49 | 0.55 | 0.55 |
| Obs. | 73 | 73 | 73 | 73 | 73 |

Notes: Standard errors are in parentheses. White's heteroskedasticity correction was used. *** Significantly different from 0 at the 1% level. ** Significantly different from 0 at the 5% level. * Significantly different from 0 at the 10% level.

estimate on $Y/L_{1960}$ is negative and significant at the 1% level, the estimate on $s_k$ is positive and insignificant, the estimate on $(n + g + \delta)$ is negative and significant at the 1%, and the coefficient on $s_h$ is positive and significant at the 1% level. Our results are consistent with previous studies and support the hypothesis of conditional convergence.

We proceed by including our variable of interest, infant mortality, in the growth regression (specification 2). The estimate on $infant$ is negative but only significant at the 10% level, the estimates on $s_h$ and $(n + g + \delta)$ have the expected signs and are significant, and the coefficient on $s_k$ is insignificant. When we add government consumption in specification 3, we notice that

the estimate $infant$ is again significant and negative, the estimate on government consumption is negative and insignificant, and the other estimates have the expected signs and are significant. More interesting, in specification (4) we add $GiniF$ and obtain an insignificant estimated coefficient. We see that the estimate on $infant$ stays negative and significant. Our results show that an increase in infant mortality by 1% leads to a reduction in growth by 0.36 percentage points. We conjecture that female human capital inequality is one of the determinants of infant mortality and although the estimate on $GiniF$ is insignificant to growth due possibly to endogeneity problems, the estimate on $infant$ remains negative and significant at the 5% level.[15]

Next, we examine the indirect effect of female human capital inequality on economic growth. We argue that female human capital inequality affects economic growth via its impact on infant mortality as follows:

$$\text{Gini Female} \Longrightarrow \text{Infant Mortality} \Longrightarrow \text{Growth}$$

We therefore test this hypothesis by formulating the following structural model:

$$Growth = \alpha + \beta \ln(Infant) + \mathbf{Z}\eta + \varepsilon \tag{8}$$

$$\ln(infant) = \gamma + \delta\ Growth + \mathbf{X}\phi + \upsilon, \tag{9}$$

where $\mathbf{X}$ and $\mathbf{Z}$ denote two sets of additional explanatory variables. The equation of interest is equation (8); specifically, we want to know whether infant mortality has a direct effect on Growth. To estimate equation (8) it is important that the order and rank conditions for identification are met. We further argue that female human capital inequality affects economic growth only through its effect on infant mortality.

The recent literature on income levels has proposed several historical or geographic instruments. Hall and Jones (1999) argued that European influence affects income only through its effect on "social infrastructure" and can be used as an instrument of social infrastructure on growth. Following

[15]Once again, we have considered various other control variables (results not presented to save space) and shown our results are qualitatively unaffected. For example we have interacted $GiniF$ and $infant$ to allow infant mortality to depend on the degree of female human capital inequality. The coefficient is insignificant. The estimate on infant mortality stays negative and significant. All other estimates have the expected signs and there is not a big change in terms of the significance level. We also added three dummy variables to represent Latin America, sub-Saharan Africa and Asia. The dummy variables for Latin America and sub-Saharan Africa have negative and significant estimated coefficients consistent with previous literature. The estimate on $infant$ remains negative and significant.

this literature, we consider three instrumental variables for $Infant$: *english* (the share of the population speaking English), *europe* (the share of population speaking one of the major languages of Western Europe: English, French, German, Portuguese, or Spanish), and *latitude* ( the absolute value of latitude in degrees divided by 90 and is taken from Frankel and Romer (1999)).

To examine the validity of our instruments we test the over-identifying restrictions where the endogenous variable, $infant$, is explained by the three instruments, *english*, *europe*, and *latitude*. This implies that we have two over-identifying restrictions. Specification (5) in Table 5 reports the p-value from the $\chi^2$ Sargan's test. This is a test of the joint hypothesis that the included instruments are valid instruments. We fail to reject the null of no correlation between the instruments and the error term, indicating that our over-identifying instruments are satisfactory. To evaluate the quality of our instruments, we test their validity by estimating reduced form regressions of $infant$ on the instrumental variables and the exogenous variables. We test the joint significance of the coefficients on the instruments and we are able to reject the null of zero coefficients at the 1% level of significance. This suggest that our instruments provide useful information in addition to that provided by the explanatory variables.

We present the results from this exercise in specification (5) in Table 5. Our results show that $infant$ has a negative and (albeit marginally) statistically significant effect on economic growth. Compared to the respective $infant$ estimates obtained in specifications 1-4, the 2SLS estimate is larger in magnitude. As expected, the estimate on $Y/L_{1960}$ is negative and significant at the 1% level, and the estimates on the other regressors are not significant. Our estimate of interest $GiniF$ has no direct effect on growth.

To briefly summarize, the last empirical exercise examines a new mechanism of growth. We obtain some suggestive evidence that female human capital inequality may lead to higher infant mortality which in turn reduces growth.

# 4 Conclusion

This paper provides new evidence on the effect of female human capital inequality on infant mortality and the effect of the latter on economic growth. The paper offers three contributions: First, it constructs gender-specific human capital inequality measures using the Barro and Lee (2001) education dataset. We see scope for an extensive use of this dataset on female *and* male human

capital inequality in the growth/development literature. Second, it uses these measures to examine the hypothesis that higher female human capital inequality is associated with higher infant mortally rates. Third, it considers a new channel through which female education inequality affects economic growth via its effect on infant mortality.

We find strong evidence for the first hypothesis (unequal female education increases infant mortality) and some supportive evidence that female human capital inequality may be an important obstacle to growth via its positive effect on infant mortality which is found to be negatively related to growth. Both results point to a simple but rather powerful policy implications. In deciding how to allocate aid or more specifically educational subsidies, increasing the human capital of the least educated women should receive priority, especially if reducing infant mortality is a primary goal.

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# Appendix A

Table A1: Summary statistics of relevant variables

| Country | Code | Infant | GiniF | $Y/L_{1960}$ | $Y/L_{2000}$ | Phys. | SchoolF | Malaria |
|---|---|---|---|---|---|---|---|---|
| Argentina | ARG | 35 | 0.25 | 8711.3 | 12790.55 | 3 | 6.96 | 0.09 |
| Australia | AUS | 12 | 0.16 | 12593.15 | 28479.77 | 2 | 9.93 | 0 |
| Austria | AUT | 17 | 0.26 | 8249.95 | 25820.15 | 2 | 6.59 | 0 |
| Bagladesh | BGD | 115 | 0.80 | 1329.38 | 2174.65 | 0 | 0.91 | 1 |
| Belgium | BEL | 15 | 0.21 | 8815.76 | 25233.67 | 3 | 8.27 | 0 |
| Bolivia | BOL | 116 | 0.57 | 2995.62 | 3360.68 | 0 | 4.23 | 0.34 |
| Botswana | BWA | 77 | 0.49 | 1257.05 | 4391.11 | 0 | 3.54 | 0.76 |
| Brazil | BRA | 70 | 0.45 | 3032.1 | 8609.03 | 1 | 3.49 | 0.89 |
| Cameroon | CMR | 107 | 0.69 | 2107.24 | 2592.84 | 0 | 1.86 | 1 |
| Canada | CAN | 13 | 0.29 | 12475.1 | 29408.37 | 2 | 10.14 | 0 |
| C. Afri. Rep. | CAF | 122 | 0.87 | 2697.12 | 2230.58 | 0 | 0.84 | 1 |
| Chile | CHL | 35 | 0.28 | 4798.46 | 11531.51 | 1 | 6.18 | 0 |
| Colombia | COL | 49 | 0.40 | 3291.72 | 7028.28 | 1 | 4.27 | 0.74 |
| Costa Rica | CRI | 34 | 0.33 | 4556.99 | 7382.88 | 1 | 5.02 | 0.21 |
| Denmark | DNK | 11 | 0.25 | 12576.14 | 29214.81 | 3 | 8.83 | 0 |
| Dom. Rep. | DOM | 77 | 0.49 | 2213.66 | 6269.87 | 1 | 3.71 | 1 |
| El Salvador | SLV | 79 | 0.50 | 4272.25 | 5655.84 | 0 | 3.18 | 0.98 |
| Finland | FIN | 8 | 0.21 | 8833.28 | 26137.43 | 2 | 7.51 | 0 |
| France | FRA | 13 | 0.26 | 9012.38 | 24837.32 | 3 | 6.34 | 0 |
| Ghana | GHA | 92 | 0.77 | 1114.3 | 1743.42 | 0 | 1.72 | 1 |
| Greece | GRC | 20 | 0.34 | 4805.43 | 16211.37 | 3 | 5.74 | 0 |
| Guatemala | GTM | 79 | 0.65 | 3044.46 | 4686.98 | 0 | 2.16 | 0.83 |
| Honduras | HND | 78 | 0.51 | 2202.64 | 2619.72 | 0 | 2.80 | 0.27 |
| Hong Kong | HKG | 12 | 0.44 | 3885.03 | 28985.27 | 1 | 6.53 | 0.5 |
| India | IND | 102 | 0.78 | 1057.29 | 3029.63 | 0 | 2.03 | 0.38 |
| Indonesia | IDN | 90 | 0.56 | 1170.83 | 4309.68 | 0 | 2.78 | 0.91 |
| Ireland | IRL | 14 | 0.21 | 6077.69 | 29673.53 | 2 | 7.78 | 0 |
| Israel | ISR | 17 | 0.29 | 6757.7 | 19731.21 | 3 | 8.38 | 0 |
| Italy | ITA | 19 | 0.32 | 7870.53 | 23409.35 | 4 | 5.55 | 0 |
| Jamaica | JAM | 38 | 0.25 | 3466.06 | 4398.9 | 0 | 4.26 | 0 |
| Japan | JPN | 10 | 0.20 | 5352.21 | 26607.24 | 2 | 8.07 | 0 |
| Jordan | JOR | 39 | 0.65 | 2938.15 | 4764.41 | 1 | 3.55 | 0 |
| Kenya | KEN | 86 | 0.63 | 1057.9 | 1660.26 | 0 | 2.20 | 1 |
| Korea, Rep. | KOR | 32 | 0.37 | 1890.55 | 17871.16 | 1 | 6.66 | - |
| Malawi | MWI | 161 | 0.61 | 543.02 | 1051.85 | 0 | 1.80 | 1 |
| Malaysia | MYS | 30 | 0.53 | 2732.36 | 11881.36 | 0 | 3.89 | 0.88 |
| Mali | MLI | 169 | 0.94 | 1254.45 | 1266.79 | 0 | 0.31 | 0.80 |
| Mauritania | MRT | 130 | 0.67 | 1335.74 | 1980.26 | 0 | 1.85 | 0.78 |
| Mexico | MEX | 56 | 0.42 | 5157.89 | 10517.05 | 1 | 4.51 | 0.13 |
| Mozambique | MOZ | 156 | 0.77 | 1982.94 | 1220.98 | 0 | 0.40 | 1 |
| Nepal | NPL | 129 | 0.92 | 962.16 | 1916.18 | 0 | 0.47 | 0.58 |
| Netherlands | NLD | 10 | 0.18 | 10876.95 | 26779.49 | 2 | 7.62 | 0 |
| N. Zealand | NZL | 14 | 0.19 | 13810.97 | 21675.12 | 2 | 10.70 | 0 |
| Nicaragua | NIC | 82 | 0.56 | 3783.31 | 2262.5 | 0 | 3.19 | 0.13 |
| Niger | NER | 152 | 0.93 | 2054.86 | 1147.25 | 0 | 0.31 | 0.77 |

Table A1: Summary statistics of relevant variables (cont.)

| Country | Code | Infant | GiniF | $Y/L_{1960}$ | $Y/L_{2000}$ | Phys. | SchoolF | Malaria |
|---|---|---|---|---|---|---|---|---|
| Norway | NOR | 10 | 0.17 | 9463.86 | 30064.78 | 2 | 8.48 | 0 |
| Pakistan | PAK | 123 | 0.85 | 810.79 | 2373.3 | 0 | 1.33 | 0.80 |
| Panama | PAN | 37 | 0.34 | 2972.48 | 7183.22 | 1 | 6.37 | 0.89 |
| Papua N.G. | PNG | 92 | 0.69 | 2728.78 | 3911.93 | 0 | 1.42 | 0.95 |
| Paraguay | PRY | 45 | 0.31 | 3148.7 | 5870.3 | 1 | 4.73 | 1 |
| Peru | PER | 81 | 0.48 | 4118.79 | 5509.87 | 1 | 4.89 | 0.53 |
| Philippines | PHL | 63 | 0.36 | 2633.35 | 4290.72 | 0 | 6.14 | 0.79 |
| Portugal | PRT | 33 | 0.51 | 4014.21 | 17372.31 | 2 | 3.38 | 0 |
| Senegal | SEN | 114 | 0.75 | 1338.46 | 1555.28 | 0 | 1.50 | 1 |
| Sierra Leone | SLE | 191 | 0.87 | 2756.36 | 12319.64 | 0 | 1.06 | 1 |
| Singapore | SGP | 14 | 0.49 | 6205.21 | 9009.19 | 1 | 4.88 | 0 |
| Spain | ESP | 18 | 0.28 | 5374.52 | 19526.76 | 3 | 5.28 | 0 |
| Sri Lanka | LKA | 34 | 0.39 | 1696.02 | 4135.5 | 0 | 4.90 | 0.19 |
| Sweden | SWE | 8 | 0.24 | 11425.35 | 25994.72 | 3 | 9.19 | 0 |
| Switzerland | CHE | 11 | 0.24 | 16985.64 | 28795.71 | 2 | 8.81 | 0 |
| Syria | SYR | 66 | 0.70 | 1803.3 | 5126.3 | 1 | 2.52 | 0.23 |
| Thailand | THA | 54 | 0.37 | 1412.79 | 7888.54 | 0 | 4.41 | 0.90 |
| Togo | TGO | 113 | 0.76 | 1140.31 | 1121.38 | 0 | 1.08 | 1 |
| Tr.&Tobago | TTO | 34 | 0.25 | 5569.74 | 12713.71 | 1 | 6.31 | 0 |
| Tunisia | TUN | 69 | 0.70 | 2546.42 | 8021.32 | 1 | 2.04 | 0.76 |
| Turkey | TUR | 93 | 0.62 | 3385.51 | 8031.86 | 1 | 2.54 | 0.31 |
| Uganda | UGA | 110 | 0.64 | 729.18 | 1233.64 | 0 | 1.45 | 1 |
| U. K. | GBR | 13 | 0.19 | 10947.38 | 24535.04 | 2 | 8.35 | 0 |
| USA | USA | 15 | 0.23 | 14527.6 | 37255.59 | 2 | 10.64 | 0 |
| Uruguay | URY | 31 | 0.31 | 6823.21 | 10989.42 | 2 | 6.54 | 0 |
| Venezuela | VEN | 38 | 0.41 | 10188.71 | 7726.34 | 1 | 4.65 | 0.28 |
| Zambia | ZMB | 108 | 0.53 | 1557.93 | 1152.75 | 0 | 2.95 | 1 |
| Zimbabwe | ZWE | 79 | 0.49 | 1595.46 | 3191.33 | 0 | 2.60 | 1 |

# Appendix B

**Countries in Geographic Regions**

**South East Asia & Pacific**

Afghanistan, Australia, Bangladesh, China, Fiji , Hong Kong , India, Indonesia, Japan, Korea, Malaysia, Myanmar (Burma), Nepal, New Zealand, Pakistan, Papua New Guin., Singapore, Sri Lanka, Thailand

**Europe**

Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, West, Greece, Hungary, Iceland, Ireland, Italy, Netherlands, Norway, Poland, Portugal, Spain, Sweden, Switzerland, Turkey, United Kingdom, Yugoslavia

**Latin America & Caribbean**

Argentina, Barbados, Bolivia, Brazil, Chile, Colombia, Costa Rica, Dominican Rep., Ecuador, El Salvador, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Trinidad & Tob., Uruguay, Venezuela

**Middle East & North America**

Algeria, Bahrain, Egypt, Iran, I.R. of Iraq, Israel, Jordan, Kuwait, Syria, Tunisia

**North America**

Canada, U.S.

**Sub-Suharan Africa**

Benin, Botswana, Cameroon, Central Afr. R., Congo, Gambia, Guinea-Bissau, Kenya, Lesotho, Liberia, Malawi, Mali, Mauritania, Mauritius, Mozambique, Niger, Rwanda, Senegal, Sierra Leone, South Africa, Sudan, Swaziland, Tanzania, Togo, Uganda, Zaire, Zambia, Zimbabwe