Investment in Information Technology Capital and Income Inequality in the United States: An Empirical Analysis

by

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ABSTRACT

This paper empirically investigates using the annual time-series data from 1959 – 1999, employing the most recent econometric techniques of unit root testing and the Phillips-Hansen fully-modified cointegration procedure, the impact of increasing investment in information technology capital on the degree of income inequality in the United States. The empirical findings reveal that increased investment in information technology capital, along with other controlling factors, has contributed to a widening of the degree of income inequality among families, in the United States. Although, anti-poverty programs initiated by President Johnson have led to some moderate impact on the degree of income inequality, effective human capital-augmenting policies, which although are microeconomic in nature, and yet have tremendous macroeconomic implications for equity and growth are highly warranted.

I. INTRODUCTION

In recent years, economists and policy makers in the United States, are concerned with the rising incidence of poverty and increasing income inequality which have worsened the actual distribution of income in the United States over a long period of time. In addition to considering the issues of rising costs of poverty and rising inequality, in terms of the loss of output, increasing crime rates, voters' apathy, and losses in inter-personal utility levels of the citizens who care about income inequality, the continuing attempts to eradicate poverty, hunger, and marked income inequality in the United States have become matters of social and political

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responsibility of the electorate. This concern is evident by the initiation of the war on poverty by President Johnson in 1964. An examination of the U.S. data on the observed Gini coefficient for families reveals that the degree of income inequality in the United States has been steadily rising. The Gini coefficient, which is a widely used measure of income inequality, has risen in the United States, from 0.361 in 1959 to 0.428 in 1999 [see U.S. Bureau of the Census (2002)]. A Gini coefficient of zero and one indicate, respectively, a complete egalitarian society and a society with a perfect inequality. It should be noted that the larger the actual Gini coefficient, the greater the income inequality and the smaller the actual Gini coefficient, the lower the income inequality.

Since the U.S. electorate has given a strong mandate to its representatives that the existing market-determined distribution of income be modified to establish a reasonably fair degree of equity in the economy, economists and policy analysts are busily engaged in designing anti-poverty and income redistribution policies. Designing and implementing these income-redistribution policies necessitate an understanding, quantification and identification of the factors that affect the degree of income inequality over the long-run. One of the factors that has been attributed to rising Gini coefficient in the U.S. especially in recent decades, is the rising investment in information technology capital which is said to have raised the wages of workers with technology skills, resulting from the increased demand for their labor. In recent years, many economists maintain that increased investment in information technology capital, which propelled a rapid computerization of the work place and industry especially in the 1980s and 1990s, has been instrumental in precipitating skill-biased technological change. The increased demand for highly skilled workers and the consequent escalation of premium on wages of skilled workers, have contributed to worsening of income inequality [see Katz and Murphy (1992), Krueger (1993), Autor, Katz and Krueger (1998, 1999), Brown and Campbell (2002) and Wolff (2002)].

The impact of the technological change on the structure of wages of the skilled and unskilled workers and the consequent shift in the degree of income inequality depends on whether the scale effect or the substitution effect dominates. The scale effect refers to the effect of a technological change on the demand for products that firms and industries produce, and the substitution effect indicates the impact of the technological change on the firms and industries demand for skilled workers with technical and computer skills [see Brown and Campbell (2002)]. A majority of the existing studies on the changing structure of wages assumes that in the United States during the period, 1970 – 1998, the substitution effect has outweighed the scale effect, resulting in skill-biased technological change which is almost imminent. Furthermore, there is one more view which states that personal and mainframe computers and other information technology capital goods complement the skills of highly skilled and technologically knowledgeable workers and hence increase their productivity and wages. This phenomenon is apparent in the data on increasing average returns to education and experience, which can be construed as proxies for improved skills. Using the national individual level U.S. data, from 1960 through 1990s, Bound and Johnson (1992), Levy and Murnane (1992) and Katz and Murphy (1992) have presented some empirical findings which support the hypothesis that the substitution effect of technological changes, has resulted in escalation of wages of the skilled labor-group at the industry sector level. Recently, Autor, Katz and Krueger (1998) have demonstrated, combining the individual level data with industry-level technology variables, that in the 1980s, the labor markets in the United States have undergone skill-biased technological change.

Although there have been many studies dealing with the impact of increasing investment in information technology capital on income inequality, no systematic attempt using recent developments in time-series econometrics, has been undertaken to quantify the impact of increased investment in information technology capital on the U.S. Gini coefficient for families. Information technology capital is different from other forms of capital, because it has the potential to accentuate the degree of income inequality, especially in the short-run, through its impact on the wage and employment structure in the economy. Therefore, this paper attempts to fill in this void by employing the most recent cointegration procedure, for the first time in the literature, to discern whether there exists a long-run equilibrium economic relationship between the Gini coefficient for families (GINIF), and the investment in information technology capital, as measured by the ratio of information technology capital stock to total capital stock (ITCR), over the period of 1959 – 1999. In order to control GINIF, for the effects of other relevant economic variables, such as the U.S. unemployment rate (UR), inflation rate (INFR), real GDP per capita (PRGDP), and a dummy variable (D_{64}) indicating the antipoverty programs initiated by President Johnson in 1964. These control variables are the variables which are often incorporated in other studies cited above. The objectives of the paper are to determine using the annual time-series data, whether ITCR and GINIF are cointegrated and to test whether increasing investment in information technology capital has contributed to the widening of income inequality in the U.S. during the period 1959 – 1999.

II. THEORETICAL SPECIFICATION

In light of the theoretical discussions presented above, availability of the data and a review of the literature, we specify the following estimable equation:

$$GINIF_t = \beta_0 + \beta_1 UR_t + \beta_2 INFR_t + \beta_3 PRGDP_t + \beta_4 ITCR_t + \beta_5 D_{64} + \mu_t \tag{1}$$

In the above specified equation (1), it is hypothesized that $\beta_o > 0; \beta_i \gtrless 0$ and μ_t is the stochastic disturbance term associated with equation (1). It is expected that $E(\mu_t) = 0, E(\mu_t^2 = \sigma^2)$, $E(\mu_t \mu_{t-1}) = 0$ and finally, $E(x_t \mu_t) = 0$. Thus, we assume that $\mu \sim IN(0, \sigma_\mu^2)$. To estimate equation (1), we use the most recent single-equation cointegration procedure, the Phillips-Hansen fully-modified cointegration technique (FM-OLS). The Phillips-Hansen FM-OLS procedure (1990) is chosen over the much well-known, Johansen-Juselius cointegration technique (1990), because the FM-OLS cointegration procedure corrects for endogeneity and contemporaneous correlation. The implied economic structural relationship, in the present context, also favors the use of a single-equation cointegration procedure. Hargreaves (1994) has demonstrated that in small samples, the FM-OLS cointegration estimator is a fully efficient method of estimating long-run economic equilibrium relationships.[1] Furthermore, the Johansen-Juselius technique has been found to be very sensitive to lags in the specified vector error correction model.

The data on the Gini coefficient for families are gathered from *Historical Tables for Families* [see United States Census Bureau (2002)]. The data on the unemployment rate, inflation rate, and real GDP per capita in 1996 dollars are taken from *The Economic Report of the President 2002* [see U.S. Government Printing Office (2002)]. The data on the ratio of investment in information technology capital stock to total capital stock (ITCR) are obtained from Jorgenson (2001). The ratio of information technology investment to total capital stock, rather than the absolute level of information technology capital stock is used, because a relatively rapid rate of growth of non-information technology capital stock may not enable us to discern the

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[1]For details, see Hargreaves (1994).

full effect of IT capital stock on the degree of income inequality. The results using the data on the absolute level of information technology yield basically similar and consistent results. ITCR data are expressed in current dollars, which reflect the continuous annual quality improvement of personal computers, software and office equipment over the sample data.[2] During the period under investigation, information capital stock, in current dollars, increased from 1.5% of the total capital stock to 4.35% of the total capital stock, although in 1990's it has accelerated markedly [see Jorgenson (2001)].

III. ESTIMATION RESULTS

A requisite for cointegration analysis is that the time-series of the variables, used for estimation be investigated for the presence of a unit root. The presence of a unit root in a time-series x_t reveals that the moments of the series, such as the mean and variance are time-variant or non-stationary. A non-stationary series in levels, is designated as I(1), and a stationary series in its first differences is indicated as I(0). Regressing one non-stationary series on other non-stationary series, would lead to a spurious regression. If several time-series, although non-stationary individually, yet stationary collectively and drifting together as a set, are said to be cointegrated. Cointegration amounts to a phenomenon which indicates that the variables, although are I(1) individually, together they are I(0), and thus it shows a long-run equilibrium relationship among them.

A detailed econometric analysis is conducted using a battery of unit roots which include the Augmented Dickey-Fuller (ADF) test (1976), Phillips-Perron test (PP) (1988), the most recent Kwiatkowski-Phillips-Schmidt-Shin (KPSS) (1992) and the GLS-DF test [see Elliot,

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[2] ***The findings are highly consistent, and basically similar in terms of the magnitude and statistical significance, with estimation done using the variables expressed in 1996 dollars.***

Rothenberg and Stock (1996)]. While the ADF, PP and the GLS-DF tests state the null hypothesis of non-stationarity or the presence of a unit root, the KPSS test defines stationarity as the null.[3] Stock and Watson (2003) advocate for the use of the GLS-DF test on the grounds that it is a much more statistically powerful test than the traditional ADF test and hence it is much more likely to reject the null hypothesis of the presence of a unit root, against the alternative of stationarity, when the alternative hypothesis is true. Since no single unit root test is without some statistical shortcomings, in terms of size and power properties, it is prudent to conduct a battery of unit root tests to infer an overwhelming evidence to statistically determine the order of integration of the time-series used in cointegration analyses.

The empirical results, from various unit roots tests discussed above, for the level and first-differenced, GINIF, UR, INFR, PRGDP and ITCR, are reported in Table 1. The results, from Table 1, clearly show that all the variable-series are non-stationary in levels and stationary in first-differences. While the results of ADF, PP, and DF-GLS unit root tests fail to reject the null hypothesis of non-stationarity at the 5% level of significance, the KPSS test results emphatically reject the null of stationarity around a deterministic trend at the 10% level of significance. For the first-differenced series, the results of all these unit root tests indicate that they are stationary and thus these series do not contain a unit root.[4] The determination of the order of integration of the series, in column 6 of Table 1 is based on the discussion of unit root tests presented earlier.

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[3] ***For details on unit root testing, see Maddala and Kim (1999). Unit root tests do include deterministic components of an intercept and trend.***

[4] ***Unit root testing and cointegration analysis are conducted using MICROFIT 4.0 [Pesaran and Pesaran (1997) and confirmed using EVIEWS 4.1 (2002)].***

TABLE 1

Unit Root Tests

Series	ADF	PP	KPSS	DF-GLS	Determination
GINIF	-1.92(0)	-1.69(9)	0.22(4)	-1.57(0)	I(1)
UR	-2.36(1)	-1.93(3)	0.15(4)	-2.53(1)	I(1)
INFR	-1.67(2)	-1.54 (14)	0.19(4)	-2.55(1)	I(1)
PRGDP	-2.28(1)	-1.66 (3)	0.23(4)	-1.16(4)	I(1)
ITCR	-1.16(1)	-1.01(3)	0.14(5)	-1.15(9)	I(1)
ΔGINIF	-6.44(1)	-7.99(12)	0.08(4)	-5.75(1)	I(0)
ΔUR	-4.87(1)	-4.59(9)	0.08(4)	-5.01(1)	I(0)
ΔINFR	-6.54(1)	-5.24(12)	0.07(4)	-6.50(1)	I(0)
ΔPRGDP	-4.72(0)	-4.59(9)	0.08(4)	-4.59(0)	I(0)
ΔITCR	-3.46(0)	-3.50(1)	0.09(3)	-3.63(0)	I(0)

NOTE: The critical values at the 5 percent significance level for the ADF, PP and DF-GLS unit root tests are respectively, -3.51, -3.51 and –3.19. The upper $\hat{n}_t$ value for the KPSS statistic is 0.146 at the 5 percent level. Lags in parentheses [see Fuller (1976), Phillips-Perron (1988), Elliot et al. (1996) and Kwiatkowski (1992)].

Table 2 reports the long-run cointegrating relationship, specified by (1), estimated as equation (2), by the Phillips-Hansen FM-OLS procedure based on a Bartlett window lag length of 2. Hakkio and Rush (1991) have demonstrated that the ability of cointegration tests to detect cointegration depends on total sample length or span, rather than the frequency of data. For obtaining the FM-OLS cointegration estimators, Bartlett window lags are necessary for constraining the long-run variance matrix [see Phillips and Hansen (1990)]. Since we are attempting to determine whether these series are cointegrated, it is appropriate to use level variables in estimating equation (1). Using the first-differenced dependent and explanatory

TABLE 2

The FM-OLS Results

$$GINIF_t = \underset{(54.29)^*}{29.46} + \underset{(2.04)^{**}}{0.13UR_t} - \underset{(-3.79)^*}{0.15INFR_t} + \underset{(2.45)^{**}}{0.002PRGDP_t} + \underset{(2.86)^{**}}{2.04ITCR_t} - \underset{(-7.21)^*}{2.87D_{64}} \qquad (2)$$

ADF[0] = -4.53*;	Phillips-Perron [2] = -4.46*
DF-GLS[0] = -4.64*;	KPSS [0] = 0.09***

NOTE: t-values in parentheses. Lags in brackets. *, **, and *** denote statistical significance at the 1, 5, and 10 percent levels, respectively. For estimating equation (2), a Bartlett window lag length of 2 is used.

variables in a regression model, intended to capture the long-run equilibrium economic relationship, misses out on the low frequency (long-run) information. The results, using other lag lengths are generally robust and yield consistent results. In Table 2, the calculated t-values are presented within the parentheses.[5] The empirical findings reveal that GINIF, UR, INFR, PRGDP and ITCR do form a long-run cointegrating link or relationship and thus, in the long-run, they drift together. The ADF, DF-GLS, Phillips-Perron and KPSS tests performed on the residuals, gathered from the cointegrating equation (2), indicate that the residuals are stationary and hence confirm the presence of a cointegrating relationship among the variables of interest. It is apparent in equation (2) that the regression coefficients of all the variables including the dummy variable D_{64}, reflecting income-redistributional programs to alleviate poverty, are statistically significant at the 5 percent level. The observed negative sign of the dummy variable D_{64}, indicates that as the transfer payments and expenditure on income-maintenance and other poverty-reducing programs increase, the degree of income decreases, attesting to the fact that

[5]For comparison, the results using a complementary cointegration estimator, the Johansen-Juselius procedure (1990), estimated with a VAR lag length of two, are similar and consistent. The observed trace statistic indicates the presence of a single cointegrating vector at the 1% level. The cointegrating vector, normalized on GINIF, indicates consistent results.

anti-poverty programs have been instrumental, to some extent, in redistributing income, although they might have led to some disincentive effects on work-effort. The sign and magnitude of the statistically significant efficient of UR shows that as the rate of unemployment increases, the degree of inequality will rise. This finding is à priori meaningful, as during the periods of high unemployment, it is the disadvantaged, least educated and unskilled workers who are first to be laid off and this group experiences lower earnings [see Parker (1999), Blank and Card (1993), Blank and Binder (1986), and Mocan (1999)]. The negative sign and magnitude of the coefficient of INFR depict that inflation produces a sizeable positive impact on GINIF, the higher the inflation rate, the lower the GINIF, implying that the wealth-effect of inflation is greater than the cost-of-living effect of inflation on low-income families. The cost-of-living effect of inflation refers to the declining purchasing power of the earnings and hence a lower level of real income. This finding, the wealth-effect overwhelming the cost of living effect, implies that since the majority of the low-income families are nominal debtors, they repay their debts in inflated dollars. In fact, there is some evidence to support this finding. It is estimated by the Federal Reserve's 1995 *Survey of Consumer Finances* that a typical poor household in the United States has a financial net worth of -$1,816 [see Romer and Romer (1999)]. The statistically significant sign and magnitude of the coefficient of PRGDP show that economic growth has a very minimal positive effect on GINIF. We can contend that the observed positive sign of the coefficient of PRGDP could be due to the negative effects of increased trade and the minimum wage rate increasing the unemployment rate of unskilled and teenagers, during the sample period. The sign and magnitude of the statistically significant coefficient of ITCR indicate that the increased investment in information technology capital has contributed to worsening of the income inequality problem in the United States during the period under study.

The significantly positive coefficient of ITCR variable provides some evidence which is consistent with the maintained hypothesis advanced by Katz and Murphy (1992), Krueger (1993), Autor, Katz and Krueger (1998) that computerization and technological improvements in office and computing equipment and software development, resulting from increasing ITCR has increased the demand for workers, who are skilled, and educated and who have been able to earn premium wages. The less educated and unskilled workers, on the other hand, have lagged behind with lower wages. These effects might have aggravated the income inequality situation and hence this finding lends some empirical support to the skill-biased technological change hypothesis.[6] Furthermore, in Table 2, the ADF, PP, KPSS and DF-GLS unit root tests performed on the residuals from the estimated equation (2) indicate that the residuals are stationary and thus further confirm that the variables in equation (2) are cointegrated.

Since an empirical investigation of the short-run dynamics is important for policy purposes and for further confirming the existence of a cointegrating relationship as suggested by the Granger representation theorem [see Engle and Granger (1987)], a parsimonious dynamic error-correction model is estimated, as equation (3), and the results are reported in Table 3. The error-correction term (ECT) is constructed, using the residuals from equation (2). The error-correction model (ECM) is estimated using the Ordinary Least Squares technique.

It is clear from the results presented in Table 3, that the coefficient of the lagged error-correction term ECT_{t-1}, is negative and statistically significant at the 1 percent level, which supports the

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[6] ***The results are basically similar and consistent with a double-log model, with a lag window of two:***

$$\underset{}{LGINIF_t} = \underset{(5.33)*}{2.02} + \underset{(2.93)*}{0.03LUR_t} - \underset{(-9.12)*}{0.04LINFR_t} + \underset{(2.99)*}{0.14LPRGDP} + \underset{(3.23)*}{0.14LITCR} - \underset{(-4.54)*}{0.05D_{64}}; \quad ADF(0) = -3.86*$$

****indicates statistical significance at the 5 percent and above levels. t-values in parentheses.***

TABLE 3

An Error-Correction Model

$$
\begin{aligned}
\Delta GINIF_t = & -0.04 - 0.03\Delta UR_t - 0.09\Delta INFR_t - 0.29\Delta PRGDP_t \\
& (0.12)(-0.16) \quad (-1.82)^{**} \quad (-0.70) \\
& +1.98\Delta ITCR_t + 0.24D_{64} - 0.55ECT_{t-1} \\
& (1.29) \quad (0.73) \quad (-3.69)^{*}
\end{aligned}
\tag{3}
$$

$\overline{R}^2 = 0.29$ SEE = 0.53 $n_1[1] = 0.04$ $n_2[1] = 2.77$ $n_3[2] = 26.6^*$

t-statistics in parentheses. * and ** indicate significance at the 1 and 10 percent levels, respectively. SEE is the standard error of estimate. n_1, n_2 and n_3 represent respectively, tests for serial correlation, heteroscedasticity and normality. Degrees of freedom in brackets [critical $chi.sq. = 3.84(1)$].

error-correction behavior stated by the Granger representation theorem. The coefficient of ECT_{t-1} denotes that the speed of adjustment to the long-run equilibrium is about 0.55 implying that the discrepancy in the disequilibrium of 55 percent will disappear within a year. The statistically significant error-correction term further supports the validity of cointegrating relationship in equation (2). Equation (3) passes all diagnostic tests, with the exception of normality. The statistical insignificance of most of the explanatory variables, makes sense, and should not raise any concern for alarm since the time period, under review is too short for the variables to impact GINIF. What is relevant in this context is the significance of the coefficient of ECT_{t-1}, which adds credibility to the evidence of cointegration in equation (2).[7]

[7]***An error-correction model, using the double-logarithmic specification yields similar and consistent results:***

$$
\begin{aligned}
\Delta LFINIF_t = & \ 0.03 - 0.06\Delta UR_t - 0.02\Delta LINFR_t - 0.59\Delta LPRGDP_t + 0.09\Delta LITCR_t \\
& (0.24)(-2.21)^{*} \quad (-3.35)^{*} \quad (-3.06)^{*} \quad (0.99) \\
& +0.01D_{64} - 0.56ECT_{t-1}, \overline{R}^2 = 0.46 \\
& (1.54) \quad (-4.33)^{*}
\end{aligned}
$$

****indicates statistical significance at the 5 percent level. t-values in parentheses.***

IV. CONCLUSION

In this paper, using a battery of unit root testing and the recent cointegration procedure, the Phillips-Hansen fully-modified OLS estimator, it is shown that during the period 1959 – 1999, in the United States, increased investment in information technology capital, along with other controlled factors, such as the unemployment rate, inflation rate, real gross domestic per capita and transfer payments, has contributed to a widening of income inequality, as evidenced by increasing GINI coefficient for families. Econometric tests show that in the long-run , the above mentioned variables, GINIF, UR, INFR, PRGDP, and ITCR, together form a cointegration set. An error-correction model, estimated and presented in the paper, further supports the existence of cointegration among these variables. Although, anti-poverty programs initiated by President Johnson have resulted in some moderate impact of reducing poverty and thus the degree of income inequality, effective human capital-augmenting policies, via tax incentives for individuals and businesses, which although are microeconomic in nature and yet have tremendous macroeconomic implications for equity, efficiency and economic growth are highly warranted.

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