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Diffusion of technology and its implications for income distribution in the post-Soviet countries

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This study investigates the impact of the diffusion of technology on income distribution across different income segments in post-Soviet countries. Having country and data-centric heterogeneities, this study uses the quantiles via moments approach to examine the role of the diffusion of technology on the income shares of the top 10%, middle 40%, and bottom 60% segments. Our findings depict that the diffusion of technology contributes to improving the income share of the bottom income class the most, followed by the middle group in the post-Soviet countries. Furthermore, the top income class experiences a significant inequality-reducing effect due to the diffusion of technology. Specifically, an increase in the diffusion of technology is associated with a significant decrease in the income share of the top 10% for all quantiles, with the largest coefficient observed at q.25, whereas an increase in the diffusion of technology positively and significantly related to the income share of the bottom 60% across entire quantiles (q.25–q.95), with the largest coefficient observed at q.95. Diffusion of technology is positively and significantly related to the income share of the middle 40% across the lower quantiles (q.25–q.75). Moreover, while regulatory quality shows a negative impact on the income share of the top 10% in the highest quantile (q.95), its effect on the middle and the bottom income classes is positive in our sample countries.

Introduction

The rapid diffusion of technology has been considered a significant force behind economic progress and development in recent years. The increasing significance of information and communication technology (ICT) has been emphasized by numerous researchers and global organizations. However, some researchers argue that despite the diffusion of technology's contribution to economic growth, it may significantly change the income stratification order. Some studies on the technology diffusion and income inequality nexus have reported findings that support the Skill-Biased Technical Change hypothesis, which asserts that technological advancements exacerbate wage inequality by increasing demand for highly skilled workers [2; 5; 10]. On the other hand, the findings of some investigations have nullified the validity of this hypothesis [1; 3; 4].

The impact of ICT on redistribution processes may differ among groups of countries, as distinct

Table 1. Variables and Data Sources.

Variables	Sources
Dependent Variable	
Income share of the top 10% (TOP)	World Inequality Database
Income share of the middle 40% (MID)	World Inequality Database
Income share of the bottom 60% (BOT)	World Inequality Database
Independent Variables	
Diffusion of Technology (TEC)	KOF Globalisation Index Database
GDP Per Capita (GDPC)	WDI Database
Regulatory Quality (RQ)	The Worldwide Governance Indicators

Note: The variables are transformed into logarithmic form.

groups possess varying inequality structures and distinct technology diffusion characteristics. The group of post-Soviet countries is a good focus because of their several features including having the same inequality structure and being primarily resource-abundant economies. This group of countries has experienced a considerable expansion of technology diffusion. To comprehend how this growth affects these countries' income distribution, it is significant to focus on the different income segments of the population.

Previous studies mainly utilize general inequality measures like the Gini coefficient [7; 8]. However, this approach has some important limitations, specifically when it fails to account for structural changes within the population. For example, the Gini coefficient may overestimate or underestimate the predominant income group in the population [9]. To address these limitations, this study considers various income levels, including the income share of the top 10%, the income shares of the middle 40%, and the income share of the bottom 60% as dependent variables, which provides a significant advantage to understand the distinct magnitudes of the diffusion of technology on these income segments.

Using the quantiles via moments methodology, this study aims to examine how technological progress influences the different income groups in the post-Soviet countries. The rest of the study is structured as follows: first, the data and methodology employed in the analysis are outlined, detailing the quantiles via moments methodology and the variables incorporated in the study. Second, the findings are presented concentrating on the magnitude of the coefficients for each income segment and their implications for income distribution. Finally, the last section includes a conclusion.

Data and Methodology

This study examines the role of the diffusion of technology in the different income segments, including the income shares of the top 10%, the middle 40%, and the bottom 60%, in the context of 12 post-Soviet countries. Panel data collected from 1991 to 2019 is utilized for the analysis. Table 1 provides an overview of the variables, definitions, and data sources. We employ different income group measures to better understand which income segments benefit or suffer from the diffusion of technology, which is not possible using the Gini coefficient. The income share of the top 10% represents the percentage of total income received by the highest and upper-middle income percentiles. Moreover, the income share of the middle 40% represents the total income received by the middle-income group. Lastly, the income share of the bottom 60% accounts for the six lowest deciles.

We utilize the quantiles via moments technique developed by Machado & Santos Silva [11] to estimate the econometric model, addressing several crucial factors. Firstly, the variables exhibit substantial heterogeneity across countries and over time. Secondly, this approach allows for the application

Table 2. Descriptive Statistics.

Variable		Mean	Std. Dev.	Min	Max
TOP	overall	0.4119681	0.0543499	0.2501	0.5212
	between		0.0488071	0.339769	0.483431
	within		0.0276406	0.2075957	0.4970991
MID	overall	0.4200359	0.0285084	0.3487	0.4899
	between		0.0264762	0.3894965	0.4773
	within		0.0129731	0.3792394	0.5014394
BOT	overall	0.2308543	0.0388897	0.1516	0.3669
	between		0.0332217	0.1784241	0.2888655
	within		0.022311	0.1680267	0.3833267
TEC	overall	3.929352	0.3157014	3.138709	4.419752
	between		0.1397447	3.650342	4.109545
	within		0.2858577	3.266468	4.417483
GDPC	overall	7.815646	0.812418	5.949625	9.402827
	between		0.7290448	6.528235	9.069444
	within		0.405956	6.893957	8.622291
$GDPC^2$	overall	61.74242	12.70989	35.39803	88.41316
	between		11.39072	42.74332	82.32849
	within		6.379704	47.58291	75.31585
RQ	overall	−0.6553264	0.7080451	−2.133038	1.125411
	between		0.6737932	−1.94496	0.1626995
	within		0.2893331	−1.83249	0.3073852

of techniques that are accurate only for estimating conditional means, such as distinguishing cross-sectional effects in panel data-based empirical models, while also providing insights into how the regressors influence the overall conditional distribution [6].

$$Y = \alpha + X'\beta + \sigma\left(\delta + Z'\gamma\right)U \quad (1)$$

where Y stands for the vector of dependent variables, while X' signifies the vector of independent variables. The slope coefficients are represented by β, and Z is the k-vector that comprises known differentiable (with probability 1) transformations of the components of X, where l denotes an individual element.

$$E(U) = 0 \text{ and } E\left(|U|\right) = 1 \quad (2)$$

$$Q_y\left(\tau|X\right) = \alpha + X'\beta + \sigma\left(\delta + Z'\gamma\right)q(\tau) \quad (3)$$

Where $q(\tau) = F_U^{-}(\tau)$, so $\Pr\left(U < q(\tau)\right) = r$

$$Q_y\left(\tau|X\right) = \alpha + \delta q(\tau) + X'(\beta + \gamma q(\tau)) \quad (4)$$

$$\beta_l(\tau, X) = \beta_l + q(\tau)D_{X_l}^{\sigma} \quad (5)$$

$$D_{X_l}^{\sigma} = \frac{\partial\sigma(\delta + Z'\gamma)}{\partial X'} \quad (6)$$

Table 3. Findings for Model 1: Income Share of the Top 10% (TOP).

Variables	location	scale	qtile_25	qtile_50	qtile_75	qtile_95
TEC	−0.077***	0.0192**	−0.095***	−0.074***	−0.059***	−0.045***
	(0.0158)	(0.0091)	(0.0207)	(0.0155)	(0.0145)	(0.0170)
GDPC	−0.0887*	0.0959***	−0.177**	−0.0741	0.0032	0.0704
	(0.0537)	(0.0310)	(0.0702)	(0.0533)	(0.0491)	(0.0584)
GDPC2	0.0072**	−0.0060***	0.0128***	0.0063*	0.0014	−0.0027
	(0.0034)	(0.0019)	(0.0044)	(0.0034)	(0.0031)	(0.0037)
RQ	−0.0037	−0.0042	0.0001	−0.0044	−0.0078	−0.0108*
	(0.0053)	(0.00310)	(0.00704)	(0.00522)	(0.00494)	(0.00574)
Constant	0.968***	−0.416***	1.353***	0.904***	0.569***	0.277
	(0.200)	(0.116)	(0.261)	(0.201)	(0.182)	(0.219)

Note: Significance levels of the coefficients are *** and * for the 1% and 10% levels, respectively. Standard errors are in ().

Table 4. Findings for Model 2: Income Share of the Middle 40% (MID).

Variables	location	scale	qtile_25	qtile_50	qtile_75	qtile_95
TEC	0.0205**	0.000951	0.0195***	0.0204***	0.0215*	0.0223
	(0.0080)	(0.0046)	(0.0069)	(0.0076)	(0.0111)	(0.0144)
GDPC	0.0938***	0.0367**	0.0550**	0.0883***	0.130***	0.162***
	(0.0289)	(0.0168)	(0.0252)	(0.0281)	(0.0401)	(0.0523)
GDPC2	−0.0068***	−0.0022**	−0.004***	−0.0064***	−0.0090***	−0.010***
	(0.0018)	(0.0010)	(0.0016)	(0.0018)	(0.0025)	(0.0033)
RQ	0.0033	0.0038**	−0.0007	0.0028	0.0072**	0.0105**
	(0.0026)	(0.0015)	(0.0022)	(0.0025)	(0.0036)	(0.0047)
Constant	0.0275	−0.130**	0.165*	0.0468	−0.102	−0.212
	(0.107)	(0.0622)	(0.0932)	(0.104)	(0.149)	(0.194)

Note: Significance levels of the coefficients are *** and * for the 1% and 10% levels, respectively. Standard errors are in ().

$$
\begin{gathered}
E[RX] = 0 \\
E[R] = 0 \\
E\left[(|R| - \sigma\left(\delta + Z'\gamma\right))D_{\gamma}^{\sigma}\right] = 0 \\
E\left[(|R| - \sigma\left(\delta + Z'\gamma\right))D_{\delta}^{\sigma}\right] = 0 \\
E\left[I(R \leqslant q(\tau)\sigma\left(\delta + Z'\gamma\right)) - \tau\right] = 0
\end{gathered}
\tag{7}
$$

$$
R = Y - \left(\alpha - X'\beta\right) = \sigma\left(\delta + Z'\gamma\right)U \tag{8}
$$

$$
D_{\gamma}^{\sigma} = \frac{\partial\sigma\left(\delta + Z'\gamma\right)}{\partial\gamma} \tag{9}
$$

$$
D_{\delta}^{\sigma} = \frac{\partial\sigma(\delta + Z'\sigma)}{\partial\delta} \tag{10}
$$

$$
\begin{gathered}
E[UX] = 0 \\
E[U] = 0 \\
E\left[(|U| - 1)D_{\gamma}^{\sigma}\right] = 0 \\
\left[(|U| - 1)D_{\delta}^{\sigma}\right] = 0 \\
E\left[I\left(U < q(\tau)\right) - \tau\right] = 0
\end{gathered}
\tag{11}
$$

$$
U = \frac{Y - (\alpha + X'\beta)}{\sigma(\delta + Z'\gamma)} \tag{12}
$$

Table 5. Findings for Model 3: Income Share of the Bottom 60% (BOT).

Variables	location	scale	qtile_25	qtile_50	qtile_75	qtile_95
TEC	0.0693***	0.0212	0.0514***	0.0662***	0.0910***	0.116**
	(0.0182)	(0.0170)	(0.0098)	(0.0159)	(0.0334)	(0.0543)
GDPC	0.0022	0.0882*	−0.0722**	−0.0106	0.0926	0.198
	(0.0570)	(0.0533)	(0.0309)	(0.0497)	(0.104)	(0.171)
GDPC2	−0.0011	−0.0056*	0.0036*	−0.0002	−0.0068	−0.0136
	(0.0036)	(0.0034)	(0.0019)	(0.0031)	(0.0066)	(0.0109)
RQ	0.00134	−0.0076	0.0077**	0.0024	−0.0064	−0.0155
	(0.0063)	(0.0059)	(0.0034)	(0.0055)	(0.0117)	(0.0190)
Constant	0.0059	−0.403**	0.347***	0.0649	−0.407	−0.887
	(0.215)	(0.201)	(0.116)	(0.185)	(0.386)	(0.649)

Note: Significance levels of the coefficients are *** and * for the 1% and 10% levels, respectively. Standard errors are in ().

$$Y = D'_{\beta_D} + C'_1\beta_1 + \sigma\left(D'\gamma_D + C'_1\gamma_1\right)U \tag{13}$$

$$D_l = \mathscr{D}_l\left(C_1, C_2, U^*\right) \text{ for } l = 1, \dots k_D \tag{14}$$

where $\mathscr{D}_l\,(.)\;:\;\mathbb{R}^{k_1+k_2+1} \to \mathbb{R},\;\sigma(.)$

$$X' = \left(D', C_1\right), C' = \left(C'_1, C'_2\right)$$
$$\beta' = \left(\beta'_D, \beta'_1\right) \text{ and } \gamma' = \left(\gamma'_D,\ \gamma'_1\right)$$
$$\Pr\left\{Y \leqslant S_y(\tau|X)\right\} = \Pr\left\{Y \leqslant S_y(\tau|X)|C\right\} = \tau \tag{15}$$

$$S_y\,(\tau|C) = X'\beta + \sigma(X'\gamma)q(\tau) \tag{16}$$

$$\frac{1}{\sqrt{n}}\sum_1^n C_i\left(\frac{Y_i - X_i'\widehat{\beta}}{\sigma\left(X_i'\widehat{\gamma}\right)}\right) = 0 \tag{17}$$

$$\frac{1}{\sqrt{n}}\sum_1^n C_i\left(\frac{\left|Y_i - X_i'\widehat{\beta}\right|}{\sigma\left(X_i'\widehat{\gamma}\right)} - 1\right) = o_p \tag{18}$$

$$\frac{1}{\sqrt{n}}\sum_1^n \psi_i\left(\frac{\left|Y_i - X_i'\widehat{\beta}\right|}{\sigma\left(X_i'\widehat{\gamma}\right)} - 1\right) = o_p(1) \tag{19}$$

Findings

By focusing on our variables, we initiate our investigation with descriptive statistics. Table 2 provides the descriptive statistics for the variables of M1, M2, and M3. Specifically, Table 2 displays the overall standard deviation for the variables along with within and between measurements. According to Table 2, for most of the variables, the standard deviation is profound under the between measure, which suggests country-specific heterogeneity among the variables that we consider.

The findings for Model 1, Model 2, and Model 3 are presented in Table 3, Table 4, and Table 5. Moreover, Figure 1 illustrates the response of different income groups to the diffusion of technology. According to the findings of Model 1 (Table 3), an increase in the diffusion of technology correlates with a substantial decrease in the income share of the top 10% across all quantiles (q.25–q.95). The magnitude of the coefficient is the highest at the lower quantiles (q.25), implying the increased diffusion of technology has a more effect on reducing income share of the top 10% of the population at lower quantiles. Regarding the effects of GDP per capita and the quadratic form of GDP per capita, their impacts reveal a mixed effect across the quantiles, with the highest positive impact at q.25 (−0.177) and the highest negative impact at q.25 (0.0128), indicating a non-linear relationship between GDP per capita and the income share

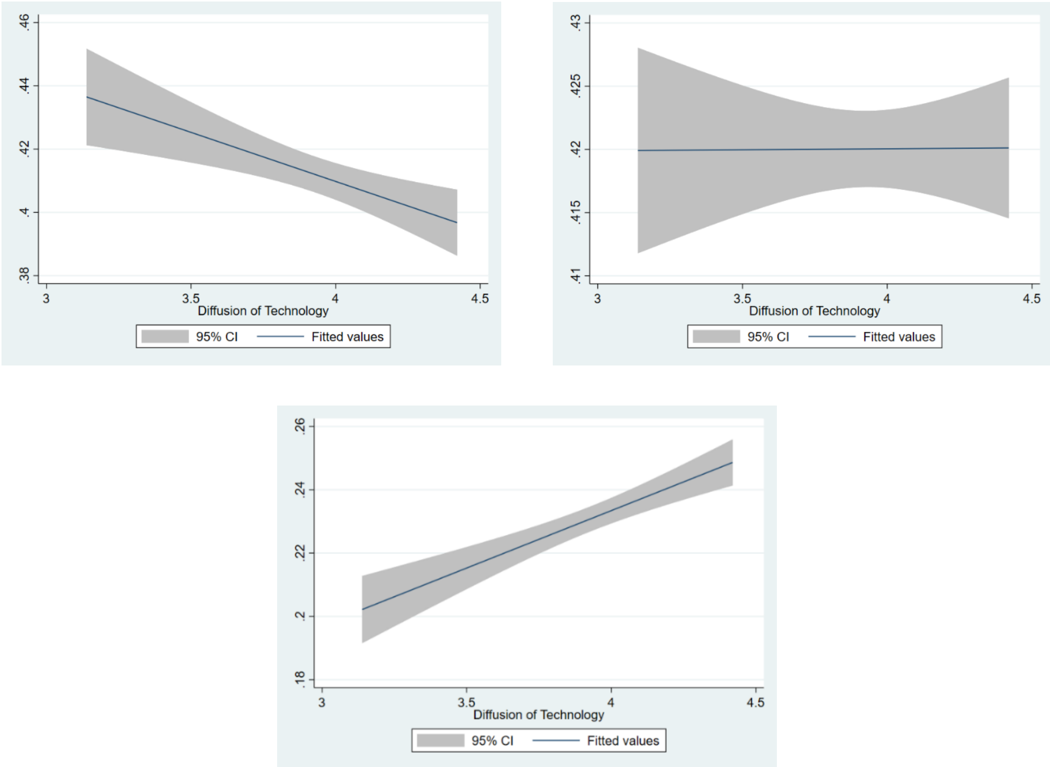

Figure 1. The response of different income groups to the diffusion of technology:
a) The response of TOP to TEC; b) The response of MID to TEC; c) The response of BOT to TEC.

of the top 10%. In addition, regulatory quality demonstrates a negative and significant impact on the income share of the top 10% in the highest quantile (q.95).

The findings of Model 2 (Table 4) reveal that a rise in the diffusion of technology has a positive and significant connection to the income share of the middle 40% across the lower quantiles (q.25–q.75) with the highest magnitude of the coefficient observed at q.75 (0.0215). GDP per capita consistently demonstrates a positive and significant association with the income share of the middle 40% with the highest coefficient observed at q.95 (0.162). Furthermore, the coefficients of regulatory quality are positive and significant at q.75 and q.95.

According to the findings of Model 3 (Table 5), an increase in the diffusion of technology has a positive and significant association with the income share of the bottom 60% across the entire quantiles (q.25–q.95). The magnitude of the coefficient is the highest at q.95 (0.116), indicating that technology diffusion has a more significant effect on the bottom income group of the population at higher quantiles.

Additionally, GDP per capita and the quadratic form of GDP per capita display mixed outcomes across the quantiles, with the negative and significant impact observed at q.25 and the positive and significant impact at q.25, respectively. This indicates a non-linear relationship between GDP per capita and the income share of the bottom 60%. Moreover, the coefficient of regulatory quality on the income share of the bottom 60% is positive and significant in q.25.

Conclusion

This study examines the role of the diffusion of technology on distinct income groups in selected 12 post-Soviet countries. The income groups are categorized into the top 10%, the middle 40%, and the bottom 60%. In this study it is employed the quantiles via moments technique because of the country and data-centric heterogeneity to investigate the impact of our variables on the income share of these groups, emphasizing the significance of the coefficients across differing quantiles. The findings reveal that an increase in technology diffusion has a positive and significant relationship with the income share of the bottom 60% throughout all quantiles. The income share of the middle 40% is positively and significantly associated with technology diffusion across the lower quantiles. Furthermore, regulatory quality negatively affects the income share of the top 10% at the higher quantiles, while it has a positive impact on the middle and bottom income groups in our sample countries.

To conclude, the top 10% income segment seems to be most affected by ICT diffusion in terms of reduced income share, particularly at lower quantiles. On the other hand, the middle 40% and bottom 60% income segments experience increased income shares due to ICT diffusion. This suggests that ICT diffusion might contribute the most to improving income distribution for the bottom income segment, followed by the middle segment, and has the most significant inequality-reducing effect on the top segment.

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