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Abstract: Income inequality could lead to weaker economic performance, and there is no consensus on how innovations could affect income inequality. In this paper, we use cross-country panel data to examine the relationship between telecommunications innovation, income inequality, and unemployment. We find different correlations between different levels of technological innovation and income inequality. Our study shows that the spread of 3G communication technologies has little impact on income inequality, while the spread of 4G communication technologies has significantly increased national income inequality. Moreover, the empirical results are robust to various measures of inequality. Finally, 3G communication technologies create far fewer new jobs than jobs displaced by automation, thus increasing unemployment levels. 4G communication technologies create more new jobs, thus reducing unemployment and increasing inequality.

Keywords: Telecommunication Innovation; Inequality; Unemployment

1. Introduction

It is widely acknowledged that the past decades have experienced a sharp increase in top income inequality, particularly in developed countries. A number of recent papers study the dynamics of top income inequality. Philippon & Reshef (2012), Bell & Van Reenen (2014), Piketty, Saez, & Stantcheva (2014) and Rothschild & Scheuer (2016) explore the possible reasons lead to rising top income inequality. Bakija et al. (2010) and Kaplan & Rauh (2010) point out that the rise in top inequality occurs across a range of occupations; it is not just focused in finance or among CEOs, but also includes doctors, lawyers and athletes. Figure 1 examines the rising trend of the GINI index from 1999 to 2019 in the U.S., China and France. There are significant differences in the trends of income inequality levels in these countries, with the income gap remaining at a low level in France, in contrast to the U.S., where it has been at a high level, and China, where the trend of income gap change has been unstable.

There is a large literature that has explored the causes that may exacerbate income inequality, such as regional policies (Martin, 1999), technical innovation (Hémous & Olsen, 2014), tax (Alstadsæter et al., 2019), economic development (Deyshappriya, 2017), race issues (Liu et al., 2017) and even environmental factors (Yang & Liu, 2018). It has been widely documented that innovation is one of the key determinates of inequality (Jones and Kim, 2018; Aghion et al., 2019). Acemoglu (2002) and Aghion et al. (2002) point out that the 'general purpose' new information technologies change lead to income inequality, of which automation lowers low-skill wages (Hémous & Olsen, 2014; Zhou & Tyers, 2019). When discussing the relationship between innovation and income inequality, patent and related citation are common measurements of innovation (Aghion et al., 2019). In recent years, internet access, as one of the nonnegligible technology innovations, has been discussed from many perspectives, such as economic growth (Arvin & Pradhan, 2014; Czernich et al., 2011; Holt & Jamison, 2009; Jiménez et al., 2014; Kolko, 2012; Koutroumpis, 2009), unemployment (Hjort & Poulsen, 2019; Jayakar & Park, 2013) and labour productivity (Mack & Faggian, 2013; Najarzadeh et al., 2014). However, most of this literature discusses the economic impact of broadband access, and little attention has been paid to the impact of communication technology innovations on income inequality, such as 3G and 4G innovations that have brought dramatic changes to human life in recent years. Figure 2 shows global smartphone sales from 2004 to 2019, and Figure 3 shows the length of time residents spend on smartphone apps each year in China. We can see that the huge increase in time spent on applications has been accompanied by a rapid increase in 4G smartphone sales.

The world is currently in the midst of a wave of proliferation and diffusion of 5G communication technology. 5G will permeate the way residents live and work, and will certainly have a huge impact on the way different groups of people live and work. The mobile phone and application have already changed the way we access information profoundly and lowered the costs of searching for information. Was the ease of searching one of the reasons for the rising income inequality?

The penetration of smartphones could affect the evolution of top income inequality. There are two possible channels that technological advances in mobile Internet might affect income inequality. One the one hand, telecommunication innovation can reduce inequality. Based on the concept of frugal innovation—the creation of faster, better and cheaper solutions for more people that employ minimal resource, the fundamental needs of most people (especially the former excluded groups) can be satisfied (Prabhu, 2017). In recent years, the investment in telecommunication has create many new jobs (Lee & Rodriguez-Pose, 2013), such as computing specialists, social media managers, digital marketers, energy engineers, software and app developers, drone operators, and YouTube content creators. The Internet plays a very important role in China's poverty alleviation efforts. Short video applications not only create new jobs for farmers, but also provide a platform for them to sell their agricultural products (Zhao, 2020). In this way, technological advances in mobile Internet have contributed to the redistribution of social income.

According to Lee & Rodriguez-Pose (2013), innovation can also eliminate regional inequality. Innovative regions tend to grow faster, and growth may benefit those with lower skill levels (Wheeler, 2004). Knowledge spillovers may allow those with fewer skills to learn from the highly skilled workers, increasing their productivity as they have a greater range of potential learning partners (Glaeser, 1999).

Some literatures have also considered the negative impact of innovation on inequality. Researchers have found that technological change tends to increase income inequality, widening income gaps between those whose jobs are displaced and those who assume new jobs (Autor et al., 2019). Skill-biased technological change has been a factor behind widening income inequality (Tyson & Spence 2017; Berger & Woff, 2017; Leduc & Liu 2019). High-skilled jobs, for which technology is a complement, will see increased wages and employment shares (Lee & Rodriguez-Pose, 2013). The innovation of information technology and internet allows successful entrepreneurs to grow their profits much more quickly than before (Asongu, 2015; Jones & Kim, 2018; Aghion et al., 2019). They will also substitute low-skilled labour, reducing employment shares for the low skilled and also their wages. Technology mainly substitute for routine semi-skilled employment, such as bookkeeping, which could more easily be automated (Autor et al., 2003; Manyika et al. 2017; Autor 2019, 2010).

However, routine non-skilled employment, such as cleaning, still required irregular, context specific activity and would be difficult to automate. The high opportunity cost of the time of skilled workers will lead to the outsourcing of traditionally home-based activities, such as childcare, caring for older people, cleaning and cooking—to those with lower skill levels (Mazzolari & Ragusa, 2007). In the new economy, the rise demand for routine non-skilled employment will increase their wage shares, but the high housing cost will also raise their living cost in cities (Lee & Rodríguez-Pose, 2016; Kemeny & Osman, 2018).

There are thus important reasons to suspect that the impact of innovation on inequality will differ between regions and technologies. In the remainder of this article, we test whether innovation in the mobile phone industry leads to inequality and whether this differs in countries and regions. This paper fills a gap in the literature by providing a new angle to understand how the innovation in smartphones industry contribute to income inequality across countries. We use a panel dataset to help explain the differences across countries in income inequality in terms of 3G and 4G smartphone penetration.

The remainder of the article is structured as follows. In Section 2 we present the empirical framework, which includes data and estimation strategy. Our main empirical results and a series of robustness regression results follow. In Section 4, we discuss the impact of telecommunication impacts on labour market. We end with some concluding remarks in Section 5.

2. The empirical framework

In this section, we present our measures of inequality and telecommunication innovation and the data used to compute these measures.

2.1 Data and measurement

Our core empirical analysis is carried out at the national level. Our dataset starts in 2000, a time range imposed by the availability of IDC (International Data Corporation) data which tracks the sales of cell phones. Another dataset is World Bank Open Data which includes the income inequality and unemployment measures.

2.1.1 Inequality and unemployment

The data on country level Gini coefficients[1] are drawn from the World Bank Open Data. From the same data source, we gather information on alternative measures of inequality: Namely, income share held by highest 10%, income share held by lowest 10%, income share held by highest 20%, income share held by second 20%, income share held by third 20%, income share held by fourth 20%, income share held by lowest 20%. Although these

[1] The Gini index measures the area between the Lorenz curve and a hypothetical line of absolute equality, expressed as a percentage of the maximum area under the line. A Gini index of 0 represents perfect equality, while an index of 100 implies perfect inequality.

data are available from 1967 to 2019, we focus on the period after 2004. We also gather country level unemployment rate (% of total labour force) from the World Bank Open Data.

2.2.2 3G and 4G market penetration

We use the cumulated 3G/4G mobile phone sales quantity over the total population to measure the 3G/4G market penetration. The data are taken from IDC for the period from 2004 to 2020. Our sales data is from IDC, a global market intelligence firm. It contains detailed information on quarterly mobile phone sales at the manufacturer-brand-model level, along with product attributes. Considering the sales of 3G mobile phones was on a declining trend since 2014, following Beaudry et al. (2010), we use the data from the start of sales of 3G/4G phones to their peak sales in 76 countries. Countries included are presented in Table A1 and Table A2 in the Appendix section.

2.2.3 Control variables

Following Xu & Reed (2021), we control for two groups of indicators in our regressions: economic development and structural differences (Mueller, 2016). As for economic indicators, we control for trade openness (the sum of imports and exports normalized by GDP), GDP per capita (current US$, in 10 thousand dollars) and urbanization which measured by urban population ratio (% of total population). Imports and export are measured by imports of goods and services (% of GDP) and exports of goods and services (% of GDP). Finally, we use the population density (people per square kilometer of land area) in each country to control for structural differences. Data sources are specified in Appendix Table A3.

Table 1 and Table 2 presents descriptive statistics for the variables used in this study. The tables show these statistics for all countries in two samples, which ranges from the start of 3G and 4G handset sales to peak sales, respectively.

Table 1. Basic descriptive statistics for 3G (2004-2017)

Variables	Observations	Mean	Standard deviation	Min	Max
GINI	313	35.97	7.87	24	63.40
Top 10	313	28.17	5.89	20.30	51.30
Last 10	313	2.72	0.85	0.90	4.50
Top 20	313	43.40	6.50	34.50	68.90
Second 20	313	11.69	2.08	4.70	14.70
Third 20	313	15.92	1.85	8	19
Forth 20	313	21.97	1.21	15.80	25.50
Fifth 20	313	7.02	1.85	2.40	10.50
3G	476	0.22	0.30	0	2.48
Population density	476	368.86	1,188.24	2.62	7,363.19
GDPP	476	2.38	2.09	0.06	10.15
Unemployment	476	6.62	4.36	0.40	27.07
Trade	476	86.14	68.15	21.33	437.33
Urban	476	69.56	19.44	18.22	100

Source: Authors' calculations using the dataset.

Table 2. Basic descriptive statistics for 4G (2007-2020)

Variables	Observations	Mean	Standard deviation	Min	Max
GINI	272	36.25	7.47	24	63
Top 10	272	28.21	5.54	19.90	50.50
Last 10	272	2.62	0.86	0.90	4.50
Top 20	272	43.49	6.12	34	68.20
Second 20	272	11.65	1.98	4.80	15.10
Third 20	272	15.98	1.74	8.20	19
Forth 20	272	22.06	1.16	16.50	25.50
Fifth 20	272	6.83	1.82	2.40	10.5
4G	576	0.60	0.77	0	5.33
Population density	500	367.65	1,213.05	2.96	7,953
GDPP	571	2.41	2.23	0.07	10.29
Unemployment	576	6.59	4.94	0.09	28.18

Trade	564	88.09	64.28	20.72	442.62
Urban	576	70.62	19.45	18.22	100

Source: Authors' calculations using the dataset.

2.2 Estimation strategy

To test the link between telecommunication innovation and inequality, we estimate the level of inequality in a country as a function of innovation, control variables, time fixed effects and national fixed effects. By including country fixed effects, we control the unobserved and time-unvarying country attributes that affect income inequality. We include the year fixed effects to control the unobserved confounding trends that affect income inequality. Hence, our main specification is

$$Inequality_{it} = \alpha_0 + \alpha_1 D_{it} + \alpha_2 X_{it} + \delta_t + \delta_i + \varepsilon_{it} \quad (1)$$

$Inequality_{it}$ is the inequality index of country i in year t, D_{it} is the 3G/4G mobile phone penetration in country i in year *t*. X_{it} is a set of control variables that may have impacts on inequality. Fixed effects regressions are well suited to study the question here since it helps control factors affecting both the development of telecommunication and income inequality. Therefore, δ_t and δ_i are the time and national fixed effect, respectively. ε_{it} is the error term. Eq. (1) measures how the income inequality in different regions respond to penetration of mobile phones. The key parameter of interest is α_1, which measures the impact of innovations in the smart phone industry on income inequality.

Besides our baseline regressions, we also examine the impact of telecommunication innovations on labour market to discuss the channels in which innovations affect inequality. $Unemployment_{it}$ describes the share of the labour force that is unemployed but available for and seeking employment of country i in year *t*. X_{it} is a set of control variables, δ_t and δ_i are the time and national fixed effect, respectively. ε_{it} is the error term.

$$Unemployment_{it} = \alpha_0 + \alpha_1 D_{it} + \alpha_2 X_{it} + \delta_t + \delta_i + \varepsilon_{it} \qquad (2)$$

There might be potential endogeneity issues in our baseline regression. The introduction and penetration of telecommunication technology may be endogenous and depend on the national economic development. Inequality tends to be high in rich countries, and there people's demand for new technology may promote the emergence and penetration of new telecommunication technology. This is consistent with the view of Comin & Hobijn (2004). They showed that in the past two centuries, of the 20 new technologies, most of them were first adopted in developed economies.

Following Winkler (2016) and Xu & Reed (2021), we address the potential endogeneity issue using an instrumental variable approach. Specifically, we use the number of years since telecommunication reform policies have been implemented in that country as instruments. We use two instrument variables: privatization and depoliticization. Data on instruments are from Howard & Mazaheri (2009). Privatization of state-owned telecommunication business is a count measure of the number of years since privatization. The determinant of privatization is defined as the year in which the government first sells a majority stake in the relevant state-owned telecommunication provider. Depoliticization leads to professionalizing the staff in making decisions about telecommunications policy and appointing technocrats instead of political staff to senior management positions. Depoliticization is often accompanied by aggressive deregulation, and rather having legislators actively participated in policy decisions, technical staff make rulings and solve issues with little public involvement.

They are suitable instruments since telecommunications' reforms aimed at improving the availability and affordability of the Internet have increased smart phone adoption across the nation. Besides, these variables do not affect income inequality directly other than through their impacts on the smart phone industry.

3. Empirical results

3.1 Telecommunication innovation and income inequality

To control the cofounding factors that may have impact on technological diffusion and national inequality, we control the population density, GDP per capita, trade openness and urbanization in our regression model. The impact of 3G and 4G technology diffusion on national income inequality are shown in Table 3 and Table 4. After adding the control variables, the empirical results are consistent with the basic regression results (see Table A4 and Table A5).

Using the 3G sample, we can see that there is no significant change in the response of the inequality index to 3G smartphone penetration. Similarly, the regression results show little change after controlling for population density, GDP per capital, trade openness and urbanization.

While using the 4G sample, the inequality indexes have a significant rise with the penetration of 4G phones. This means that the 4G technology diffusion has significantly increased income inequality across the world. The penetration of 4G communication technology aggravates income inequality mainly through the income share of top 10% and top 20%, while the income share of other income groups has decreased significantly. Therefore, the diffusion of mobile communication technology increases the income level of high-income groups, decreases the income of low-income groups. Thus, it exacerbates the income inequality.

Table 3. The impact of 3G on national inequality

	(1) GINI	(2) Top 10	(3) Last 10	(4) Top 20	(5) Second 20	(6) Third 20	(7) Forth 20	(8) Fifth 20
3G	0.0585	-0.1596	-0.0376	0.0178	-0.0402	0.0117	0.0675	-0.0803
	(0.7341)	(0.5797)	(0.1128)	(0.5901)	(0.1627)	(0.1624)	(0.1439)	(0.1922)
PopDensity	0.0285	0.0259	0.0017	0.0303	-0.0107	-0.0102*	-0.0076	-0.0002
	(0.0260)	(0.0205)	(0.0035)	(0.0212)	(0.0066)	(0.0061)	(0.0049)	(0.0064)
GDP	-0.8833***	-0.6380*	0.1112***	-0.6399**	0.1961***	0.1488*	0.0904	0.2214***

	(0.3098)	(0.3308)	(0.0363)	(0.2797)	(0.0644)	(0.0891)	(0.1142)	(0.0625)
Trade	-0.0044	-0.0099	-0.0012	-0.0055	0.0021	0.0034	0.0025	-0.0023
	(0.0149)	(0.0107)	(0.0017)	(0.0119)	(0.0042)	(0.0038)	(0.0023)	(0.0033)
Urban	-0.1898*	-0.1430	0.0368**	-0.1409	0.0321	0.0279	0.0191	0.0575**
	(0.1097)	(0.0903)	(0.0150)	(0.0897)	(0.0282)	(0.0244)	(0.0232)	(0.0276)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	47.8234***	37.1776***	-0.1036	51.3297***	10.1892***	14.5629***	21.0854***	2.8598
	(8.6002)	(7.0452)	(1.2319)	(7.0061)	(2.1625)	(1.9547)	(1.9243)	(2.2430)
N	313	313	313	313	313	313	313	313
R-squared	0.981	0.977	0.969	0.980	0.983	0.978	0.958	0.978

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

Table 4. The impact of 4G on national inequality

	(1) GINI	(2) Top 10	(3) Last 10	(4) Top 20	(5) Second 20	(6) Third 20	(7) Forth 20	(8) Fifth 20
4G	0.9067***	0.8133***	-0.0410	0.7843***	-0.2350***	-0.2371***	-0.1911**	-0.1453*
	(0.3383)	(0.2859)	(0.0475)	(0.2810)	(0.0874)	(0.0849)	(0.0831)	(0.0877)
PopDensity	0.0242	0.0051	-0.0096**	0.0109	-0.0017	0.0028	0.0014	-0.0200**
	(0.0300)	(0.0253)	(0.0042)	(0.0249)	(0.0077)	(0.0075)	(0.0074)	(0.0078)
GDP	-0.4211*	-0.1947	0.1166***	-0.2266	0.0591	0.0029	-0.0225	0.2069***
	(0.2528)	(0.2137)	(0.0355)	(0.2100)	(0.0653)	(0.0635)	(0.0621)	(0.0656)
Trade	-0.0040	-0.0018	0.0005	0.0002	0.0019	-0.0020	-0.0028	0.0026
	(0.0123)	(0.0104)	(0.0017)	(0.0102)	(0.0032)	(0.0031)	(0.0030)	(0.0032)
Urban	-0.0114	0.0080	0.0049	-0.0160	-0.0010	0.0024	0.0103	0.0144
	(0.1360)	(0.1150)	(0.0191)	(0.1130)	(0.0351)	(0.0341)	(0.0334)	(0.0353)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	33.9427***	26.5295***	3.3036**	42.6236***	11.9833***	15.9231***	21.6518***	7.9675***
	(9.9897)	(8.4425)	(1.4016)	(8.2985)	(2.5807)	(2.5079)	(2.4548)	(2.5904)
N	272	272	272	272	272	272	272	272
R-squared	0.988	0.984	0.982	0.988	0.989	0.986	0.970	0.986

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

We need to account for the possible endogeneity of our innovation measure to show that the positive correlation between innovation and income inequality at least partly reflects a causal effect of innovation on top income. Endogeneity could occur in particular through the feedback of income inequality to innovation adoption. We instrument for innovation using the number of years since telecommunication reform policies have been implemented.

Table 5 and Table 6 presents the results using two-stage-least-squares with the above-mentioned instrumental variables. The results are similar to those in Table 3 and Table 4. As for the results from 2SLS, we can see that the F-statistics are larger than 10, so both instruments are jointly significant during the first stage. We can see that the adoption of 3G mobile phones have relative minor effects on income inequality, while 3G telecommunication technology application increase the income share of the third and forth 20 group. On the contrary, the adoption and diffusion of 4G smartphone widens the income gap, which especially increase the income of top earners.

Table 5. Instrumental variable approach (3G)

	(1) GINI	(2) Top 10	(3) Last 10	(4) Top 20	(5) Second 20	(6) Third 20	(7) Forth 20	(8) Fifth 20
3G	-0.7640	-1.3596	-0.2497	-1.2425	0.3469	0.6146**	0.6021**	-0.3562
	(1.1170)	(0.9022)	(0.1641)	(0.9309)	(0.2809)	(0.2841)	(0.2543)	(0.2926)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	42.5648***	33.4892***	0.2621	45.9066***	11.6548***	15.9932***	22.0445***	3.5072
	(8.2541)	(6.6671)	(1.2127)	(6.8794)	(2.0754)	(2.0996)	(1.8793)	(2.1626)
N	252	252	252	252	252	252	252	252
F-stat	16.16	16.16	16.16	16.16	16.16	16.16	16.16	16.16
R-squared	0.979	0.976	0.961	0.979	0.982	0.976	0.956	0.974

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

Table 6. Instrumental variable approach (4G)

	(1) GINI	(2) Top 10	(3) Last 10	(4) Top 20	(5) Second 20	(6) Third 20	(7) Forth 20	(8) Fifth 20
4G	1.3062**	1.0758**	-0.1317	1.0079**	-0.3512**	-0.2522*	-0.1948	-0.3161**
	(0.5340)	(0.4517)	(0.0815)	(0.4451)	(0.1383)	(0.1353)	(0.1429)	(0.1494)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	38.9897***	33.5348***	4.0764***	47.4684***	9.5023***	13.5944***	21.0809***	10.0674***
	(7.7928)	(6.5919)	(1.1890)	(6.4947)	(2.0180)	(1.9740)	(2.0851)	(2.1804)
N	213	213	213	213	213	213	213	213
F-stat	22.28	22.28	22.28	22.28	22.28	22.28	22.28	22.28
R-squared	0.989	0.985	0.980	0.988	0.989	0.987	0.968	0.985

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

3.2 Robustness checks

In this section, we assess the robustness of our estimates by using alternative measurement of inequality and smartphone penetration. We conduct two robustness checks to our analysis: (i) alternative calibrations of inequality measurement, which is the share of sales of different categories of handsets in total sales, and (ii) using lagged explanatory variables on the right-hand side.

3.2.1 Alternative inequality measurement

Income inequality indicator choice could affect empirical results (De Maio, 2007). Here we use the detailed smartphone sales data to construct another inequality measure. We calculate the share of sales of different categories of handsets in total sales as another measure of inequality. The IDC data has the sales of handsets in different price ranges. According to IDC's Worldwide Quarterly Mobile Phone Tracker, the mobile phones are classified into 7 categories based on their price, which are Ultra-Premium ($1000+), Premium ($800-$1000), High-End ($600-$800), Mid- to High-End ($400-$600), Mid-Range ($200-$400), Low-End ($100-$200) and Ultra Low-End (<$100). Based on the classification, we class the phones into 3 class, which are High-End ($600+), Mid-range ($100-$400) and Low-End (<$100). The sample period is also from the start of 3G/4G mobile phone sales to their peak sales in those 76 countries.

The basic summary statistics are shown in Table 7 and Table 8. We can see that the price level of 3G mobile phone consumption are mainly concentrated in the middle and high level, which is between $100 and $1000. Meanwhile, 4G phones are relatively more expensive, with High-End mobiles phone sales take up the majority of 4G smartphone sales.

Table 7. 3G mobile phone sales share of different price categories

Variables	Observations	Mean	Standard deviation	Min	Max
High	476	.4746	.3402	0	1
Mid	476	.4177	.2791	0	1
Low	476	.1078	.2391	0	1

Source: Authors' calculations using the dataset.

Table 8. 4G mobile phone sales share of different price categories

Variables	Observations	Mean	Standard deviation	Min	Max
High	477	.539	.3429	0	1
Mid	477	.3969	.2844	0	1
Low	477	.0641	.0937	0	.5057

Source: Authors' calculations using the dataset.

Using the share of cell phone sales at different price levels as an alternative inequality measure, we run our main regression model, as shown in Eq. (1). The regression results are shown in Table 9 and Table 10. Generally speaking, we can see that the coefficients on 3G adoption and penetration are mostly insignificant on inequality measures, while 4G mobile phone penetration significantly promotes the consumption of high-end mobile phones, while lowers midlle range and low-end mobile phones purchases. The empirical results are consistent with our baseline regression results.

Table 9. Alternative sales share inequality measurement (3G)

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS			2SLS	
	High-End	Mid-range	Low-End	High-End	Mid-range	Low-End
3G	0.0795	-0.0557	-0.0237	-0.2226	0.2438	-0.0212
	(0.0636)	(0.0455)	(0.0519)	(0.3794)	(0.2359)	(0.3833)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-2.4579***	1.8741***	1.5838**	-1.7235***	1.6402***	1.0834
	(0.8584)	(0.6146)	(0.7009)	(0.6481)	(0.5119)	(0.8506)
N	476	476	476	358	358	358
F-stat				179.98	179.98	179.98
R-squared	0.723	0.789	0.626	0.707	0.773	0.623

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

Table 10. Alternative sales share inequality measurement (4G)

	(1)	(2)	(3)	(4)	(5)	(6)
		OLS			2SLS	
	High-End	Mid-range	Low-End	High-End	Mid-range	Low-End
4G	0.2452***	-0.1855***	-0.0597***	0.5617**	-0.4570*	-0.1048**
	(0.0267)	(0.0254)	(0.0124)	(0.2657)	(0.2673)	(0.0496)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Constant	1.5692*	0.4262	-0.9954***	0.0191	1.3818	-0.4009*
	(0.8085)	(0.7695)	(0.3752)	(1.7309)	(1.6548)	(0.2055)
N	443	443	443	312	312	312
F-stat				624.56	624.56	624.56
R-squared	0.918	0.895	0.709	0.897	0.873	0.710

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

3.2.2 Lagged explanatory variables

We also perform the robustness check to test the potential lagged effect of 3G and 4G on inequality. Considering the endogeneity issue, we also instrument for the lagged explanatory variables. Table 11 and Table 12 present results with the same variables as in Table 3 and Table 4 but using lagged explanatory variables on the right-hand side, and the 2SLS results are shown in Table 13 and Table 14.

Tables 13 still shows an insignificant result for our key explanatory variable – 3G mobile phone penetration - through all columns. Table 14 shows a positive and statistically significant result for our dependent variable – income inequality. As for the magnitude, looking at Column (1) in Table 14, we expect a 1.2% increase in the Gini coefficient when 4G mobile phone popularity increase by 1%. To put that in perspective, the benefits bring by the new technology are mostly enjoyed by the top income groups. Our results support the technology diffusion leads to top income inequality hypothesis.

Table 11. 3G mobile phone penetration and inequality - lagged explanatory variables

	(1) GINI	(2) Top 10	(3) Last 10	(4) Top 20	(5) Second 20	(6) Third 20	(7) Forth 20	(8) Fifth 20
L2.4G	-0.3584	-0.6662	-0.0177	-0.3629	0.0405	0.1040	0.2015	-0.0340
	(1.7842)	(1.3605)	(0.2513)	(1.4439)	(0.4290)	(0.4095)	(0.2790)	(0.4479)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	47.6530**	36.3441***	-0.4256	50.2380***	10.6489**	14.8194***	21.6847***	2.2956
	(18.3920)	(13.5938)	(2.4302)	(14.8676)	(4.7767)	(4.1335)	(2.8550)	(4.7889)
N	268	268	268	268	268	268	268	268
R-squared	0.984	0.980	0.972	0.983	0.985	0.981	0.961	0.981

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

Table 12. 4G mobile phone penetration and inequality - lagged explanatory variables

	(1) GINI	(2) Top 10	(3) Last 10	(4) Top 20	(5) Second 20	(6) Third 20	(7) Forth 20	(8) Fifth 20
L2.4G	1.2222***	1.2415***	-0.0236	1.1576***	-0.2869**	-0.3618***	-0.3675***	-0.1430
	(0.4281)	(0.3720)	(0.0627)	(0.3593)	(0.1110)	(0.1073)	(0.1137)	(0.1125)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	33.3047**	28.9214**	4.2943**	45.0266***	12.7306***	14.5587***	18.8642***	9.7326***
	(13.0175)	(11.3108)	(1.9050)	(10.9241)	(3.3747)	(3.2630)	(3.4587)	(3.4200)
N	221	221	221	221	221	221	221	221
R-squared	0.991	0.988	0.985	0.991	0.992	0.990	0.975	0.989

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

Table 13. 3G mobile phone penetration and inequality – instrumented lagged explanatory variables

	(1) GINI	(2) Top 10	(3) Last 10	(4) Top 20	(5) Second 20	(6) Third 20	(7) Forth 20	(8) Fifth 20
L2.4G	-2.3445	-2.9203	-0.1923	-2.6152	0.8338	1.0082	0.9107**	-0.1938
	(3.3243)	(2.3594)	(0.4395)	(2.6715)	(0.8643)	(0.7526)	(0.4339)	(0.8657)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	45.5392***	37.5346***	1.0766	50.5587***	10.7274***	14.1506***	19.4080***	3.9600
	(11.7322)	(8.5807)	(1.7160)	(9.7528)	(3.2244)	(3.1123)	(1.8192)	(3.1188)
N	213	213	213	213	213	213	213	213

F-stat	34.38	34.38	34.38	34.38	34.38	34.38	34.38	34.38
R-squared	0.982	0.978	0.966	0.981	0.983	0.977	0.957	0.978

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

Table 14. 4G mobile phone penetration and inequality - instrumented lagged explanatory variables

	(1) GINI	(2) Top 10	(3) Last 10	(4) Top 20	(5) Second 20	(6) Third 20	(7) Forth 20	(8) Fifth 20
L2.4G	1.2274*	1.4223**	-0.0614	1.1965**	-0.2215	-0.3826**	-0.5008**	-0.1650
	(0.6635)	(0.5833)	(0.1054)	(0.5657)	(0.1735)	(0.1693)	(0.1984)	(0.1884)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	34.6925***	34.2288***	5.2248***	47.3317***	11.6727***	13.3342***	17.1285***	13.4402***
	(10.7436)	(9.4445)	(1.7063)	(9.1607)	(2.8094)	(2.7406)	(3.2121)	(3.0500)
N	172	172	172	172	172	172	172	172
F-stat	15.68	15.68	15.68	15.68	15.68	15.68	15.68	15.68
R-squared	0.992	0.989	0.984	0.991	0.992	0.990	0.973	0.989

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

4. Technological diffusion and unemployment

If 3G/4G smartphone diffusion could affect income inequality, it is possible that the diffusion of smartphones has affected on the labour market, which then changed the income distribution. To test this mechanism, we consider the relationship between 3G/4G smartphone diffusion and labour market performance. Regressing top income inequality on 3G/4G smartphone diffusion at the nation level allows us to introduce both time fixed effects and country fixed effects, thereby absorbing any variation in unemployment at the country-year level. To match our cross-country analysis as closely as possible, we add controls for the population density and trade openness in Eq. (2).

We present the cross-section OLS regression and two-stage-least-squares results in Table 13. We find a positive and significant coefficient for 3G innovation, while a negative and significant relationship between 4G telecommunication innovation and unemployment rate.

The diffusion of 3G smartphones has increased the productivity of capital and labour at tasks they currently perform, but also impact the allocation of tasks to these factors of production (Acemoglu & Restrepo, 2019). However, the increase in the number of jobs created by technology is far less than the substitution of labour force (Graetz & Michaels, 2018; Acemoglu & Restrepo, 2020). Overall, the labour force *displacement effect* exceeds the *reinstatement effect*. On the contrast, the empirical results indicate that the 4G communication technologies has created enough new jobs (Frey, 2020), such as video bloggers, data maintenance personnel, software engineers and so on, most of which are frontier-technology-related (UNCTAD, 2021). Therefore, the market revenue created by frontier technology is enjoyed by those high skilled workers during the labour market disruptions.

The influence of 3G communication technology and 4G communication technology on the labour market has obvious heterogeneous effect. Compared with 3G, faster Internet technology can improve employment level (Jayakar & Park, 2013; Hjort & Poulsen, 2019), and also further improve the employment rate and wage level by promoting the information sharing of vacant positions (Bhuller et al., 2019). Therefore, we can see that the penetration of 4G can increase employment in general.

Table 13. Mobile phone popularity and unemployment

	(1) OLS	(2) 2SLS	(3) OLS	(4) 2SLS
3G	1.4948***	9.4988***		
	(0.5038)	(1.9436)		
4G			-1.1872***	-1.8332*
			(0.2178)	(1.1093)
Control variables	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Constant	9.1402***	1.6107	8.9913***	9.7246***
	(1.2364)	(3.5376)	(1.9990)	(3.2378)
N	476	358	495	350
F-stat		15.74		22.28
R-squared	0.894	0.867	0.953	0.950

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

5. Conclusion

The purpose of this paper is to investigate the impacts of 3G/4G smartphone diffusion on income distribution. Using a country-level panel dataset, we find that 3G has little impacts on income inequality, while 4G significantly widens income disparities. In addition, we also use the instrumental variables method to address the potential endogeneity issues. The results hold when we use alternative measures of inequality and lagged explanatory variables. We also examine the unemployment effect of 3G/4G smartphone diffusion. Our results show that 3G decreases employment rates, while 4G increases unemployment rates and makes the top income share even larger.

Future follow-up microeconomic research on the impacts of the smartphone adoption and diffusion on inequality and employment would explain the micro mechanism of these impacts, as the questions remain important while many economies rushing to 5G technology. Also, country-level data can be used to investigate possible causes that influence smartphone penetration and the heterogeneous impacts if smartphone diffusion. Also, it would be interesting to disaggregate income inequality by discipline and study if the association varies across different industry.

Disclosure statement

No potential conflict of interest was reported by the authors.

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Appendix

Table A1: Countries included in Table 1

Country	Frequency	Percent	Country Name	Frequency	Percent
Algeria	1	0.21	Mexico	9	1.89
Argentina	9	1.89	Morocco	1	0.21
Australia	8	1.68	Myanmar	2	0.42
Austria	9	1.89	Netherlands	9	1.89
Bahrain	1	0.21	New Zealand	5	1.05
Bangladesh	3	0.63	Nigeria	9	1.89
Belgium	9	1.89	Norway	9	1.89
Brazil	9	1.89	Oman	1	0.21
Bulgaria	2	0.42	PRC	8	1.68
Canada	7	1.47	Pakistan	10	2.10
Chile	7	1.47	Panama	1	0.21
Colombia	9	1.89	Peru	4	0.84
Costa Rica	1	0.21	Philippines	11	2.31
Czech Republic	5	1.05	Poland	7	1.47
Denmark	9	1.89	Portugal	11	2.31
Dominican Republic	1	0.21	Qatar	1	0.21
Ecuador	6	1.26	Romania	2	0.42
Egypt	6	1.26	Russia	9	1.89
El Salvador	1	0.21	Saudi Arabia	5	1.05
Finland	9	1.89	Serbia	1	0.21
France	9	1.89	Singapore	8	1.68
Germany	9	1.89	Slovakia	1	0.21
Ghana	3	0.63	South Africa	10	2.10
Greece	9	1.89	Spain	9	1.89
Guatemala	1	0.21	Sri Lanka	2	0.42
Hong Kong	8	1.68	Sweden	9	1.89
Hungary	5	1.05	Switzerland	8	1.68
India	12	2.52	Tanzania	2	0.42
Indonesia	10	2.10	Thailand	12	2.52
Ireland	9	1.89	Tunisia	2	0.42
Israel	6	1.26	Turkey	7	1.47
Italy	9	1.89	USA	8	1.68
Japan	8	1.68	Uganda	4	0.84
Kazakhstan	1	0.21	Ukraine	9	1.89
Kenya	5	1.05	United Arab Emirates	7	1.47
Korea	8	1.68	United Kingdom	9	1.89
Kuwait	5	1.05	Venezuela	8	1.68
Malaysia	11	2.31	Vietnam	6	1.26
Total	476	100.00			

Note: Frequency is the number of data points (year) of a country used in the regressions.

Table A2: Countries included in Table 2

Country	Frequency	Percent	Country Name	Frequency	Percent
Algeria	5	0.87	Mexico	8	1.39
Argentina	8	1.39	Morocco	5	0.87
Australia	8	1.39	Myanmar	6	1.04
Austria	8	1.39	Netherlands	8	1.39
Bahrain	6	1.04	New Zealand	8	1.39
Bangladesh	5	0.87	Nigeria	9	1.56
Belgium	8	1.39	Norway	8	1.39

Brazil	8	1.39	Oman	6	1.04
Bulgaria	6	1.04	PRC	8	1.39
Canada	9	1.56	Pakistan	7	1.22
Chile	8	1.39	Panama	5	0.87
Colombia	8	1.39	Peru	8	1.39
Costa Rica	5	0.87	Philippines	8	1.39
Czech Republic	9	1.56	Poland	9	1.56
Denmark	8	1.39	Portugal	8	1.39
Dominican Republic	5	0.87	Qatar	8	1.39
Ecuador	8	1.39	Romania	6	1.04
Egypt	8	1.39	Russia	10	1.74
El Salvador	5	0.87	Saudi Arabia	8	1.39
Finland	8	1.39	Serbia	6	1.04
France	8	1.39	Singapore	8	1.39
Germany	8	1.39	Slovakia	6	1.04
Ghana	5	0.87	South Africa	10	1.74
Greece	8	1.39	Spain	8	1.39
Guatemala	5	0.87	Sri Lanka	6	1.04
Hong Kong	8	1.39	Sweden	8	1.39
Hungary	10	1.74	Switzerland	8	1.39
India	8	1.39	Tanzania	5	0.87
Indonesia	8	1.39	Thailand	8	1.39
Ireland	8	1.39	Tunisia	6	1.04
Israel	8	1.39	Turkey	10	1.74
Italy	8	1.39	USA	10	1.74
Japan	9	1.56	Uganda	6	1.04
Kazakhstan	6	1.04	Ukraine	9	1.56
Kenya	8	1.39	United Arab Emirates	8	1.39
Korea	13	2.26	United Kingdom	8	1.39
Kuwait	8	1.39	Venezuela	8	1.39
Malaysia	8	1.39	Vietnam	8	1.39
Total	576	100.00			

Note: Frequency is the number of data points (year) of a country used in the regressions.

Table A3: Data Source

Variable	Definition	Source
GINI	Gini index measures the extent to which the distribution of income among individuals or households within an economy deviates from a perfectly equal distribution. A Gini index of 0 represents perfect equality, while an index of 100 implies perfect inequality.	World Bank, Development Research Group
Top 10 Last 10 Top 20 Second 20 Third 20 Forth 20 Fifth 20	Percentage share of income or consumption is the share that accrues to subgroups of population indicated by deciles or quintiles. Percentage shares by quintile may not sum to 100 because of rounding.	World Bank, Development Research Group. Data are based on primary household survey data obtained from government statistical agencies and World Bank country departments. Data for high-income economies are from the Luxembourg Income Study database.
4G/3G	Cumulated 3G/4G mobile sales over population	International Data Corporation and World Bank
Population density	Population density is midyear population divided by land area in square kilometers. Population is based on the de facto definition of population, which counts all residents regardless of legal status or citizenship--	Food and Agriculture Organization and World Bank population estimates

	except for refugees not permanently settled in the country of asylum, who are generally considered part of the population of their country of origin. Land area is a country's total area, excluding area under inland water bodies, national claims to continental shelf, and exclusive economic zones. In most cases the definition of inland water bodies includes major rivers and lakes.	
GDP	GDP per capita is gross domestic product divided by midyear population.	World Bank national accounts data, and OECD National Accounts data files.
Unemployment	Unemployment refers to the share of the labour force that is without work but available for and seeking employment.	International Labour Organization, ILOSTAT database.
Trade	The sum of imports and exports normalized by GDP. Exports and imports of goods and services represent the value of all goods and other market services provided to the rest of the world. They include the value of merchandise, freight, insurance, transport, travel, royalties, license fees, and other services, such as communication, construction, financial, information, business, personal, and government services. They exclude compensation of employees and investment income (formerly called factor services) and transfer payments.	World Bank national accounts data, and OECD National Accounts data files.
Urban	Urban population refers to people living in urban areas as defined by national statistical offices.	United Nations Population Division
Privatization Depoliticization	The number of years a country's telecommunication authority has been since privatization and depoliticization.	Howard and Mazaheri (2009)

Table A4: The impact of 3G on national inequality

	(1) GINI	(2) Top 10	(3) Last 10	(4) Top 20	(5) Second 20	(6) Third 20	(7) Forth 20	(8) Fifth 20
3G	-0.3219	-0.5138	-0.0471	-0.3245	0.0883	0.1314	0.1493	-0.0618
	(0.5607)	(0.4571)	(0.0775)	(0.4641)	(0.1386)	(0.1376)	(0.1239)	(0.1408)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	47.8234***	37.1776***	-0.1036	51.3297***	10.1892***	14.5629***	21.0854***	2.8598
	(8.6002)	(7.0452)	(1.2319)	(7.0061)	(2.1625)	(1.9547)	(1.9243)	(2.2430)
N	313	313	313	313	313	313	313	313
R-squared	0.981	0.977	0.969	0.980	0.983	0.978	0.958	0.978

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.

Table A5: The impact of 4G on national inequality

	(1) GINI	(2) Top 10	(3) Last 10	(4) Top 20	(5) Second 20	(6) Third 20	(7) Forth 20	(8) Fifth 20
4G	1.0619***	0.8773***	-0.0876*	0.8685***	-0.2538***	-0.2369***	-0.1858**	-0.2303***
	(0.3246)	(0.2727)	(0.0468)	(0.2683)	(0.0834)	(0.0810)	(0.0794)	(0.0867)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	33.9427***	26.5295***	3.3036**	42.6236***	11.9833***	15.9231***	21.6518***	7.9675***

	(9.9897)	(8.4425)	(1.4016)	(8.2985)	(2.5807)	(2.5079)	(2.4548)	(2.5904)
N	272	272	272	272	272	272	272	272
R-squared	0.988	0.984	0.982	0.988	0.989	0.986	0.970	0.986

Note: Standard deviations in parentheses. ***, **, and * respectively indicate 0.01, 0.05, and 0.1 levels of significance.