



Population aging and wealth inequality

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Received: 30 March 2023 / Accepted: 28 July 2023 / Published online: 14 August 2023

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Abstract

Much effort has been devoted to exploring the consequence of population aging on economic growth. Little attention is paid to its impact on income and wealth inequality. This is critical because inequality matters for the distribution of economic resources and social welfare and is interlinked to economic growth. To fill the void, this paper evaluates whether population aging affects inequality, with special emphasis on wealth inequality and nonlinearity. In a cross-country panel data setting, it finds that top wealth shares follow a U path, i.e., decrease and then increase, in the process of population aging. By contrast, the bottom wealth shares have an inverted-U pattern, i.e., rise and then fall, when a population ages. Similar results are reached for the income share. The data thus suggest that there exists some threshold level of population aging such that any deviations from that level will widen the gap between the wealthy and the poor and increase disparities in wealth and income inequality.

Keywords Population aging · Top wealth share · Top income share

JEL Classification D31 · E21 · J11

1 Introduction

The global population is aging. According to the World Population Prospects 2019 of the United Nations, the share of the population aged 65 and above increases from 6 in 1990 to 9% in 2019 and is projected to rise further to 16% by 2050 such that one in six people in the world will be aged 65 and above. Besides, while population aging is more common in high-income countries such as Japan and Korea, it is now apparent in the developing world such as Brazil and China. By 2050, 80% of older people will be living in low- and middle-income countries. This accelerating

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population aging driven by declining fertility and increasing longevity has posed major challenges to policymakers and alike. Challenges include adequacy of social security systems and health care as well as rising non-communicable diseases, which make fiscal sustainability difficult to maintain. There are also intensive debates about the consequence on economic growth. Some studies argue that population aging impedes economic growth via slower labor force growth and innovation as well as capital accumulation (Bloom and Luca 2016; Aksoy et al. 2019; Basso and Jimeno 2021). Others believe that an aging global population can facilitate economic growth by advancing technological progress in artificial intelligence and automation (Acemoglu and Restrepo 2017, 2022) and inducing greater female labor force participation and educational attainment (Bloom et al. 2009, 2010).

Whether population aging affects income and wealth inequality remains sparse, however. To fill this void, the paper explores the distributional repercussion of population aging, with special emphasis on wealth inequality. This is motivated by the following observations. First, wealth measures households' capacity to finance future consumption and well-being (Reinsdorf and Perozek 2004). Second, rising inequality, particularly in wealth, reflects a shift of economic resources and power from the poor to the rich. Moreover, the wealthy and powerful have stronger incentive to promote policies that produce concentrated benefits at the expense of the poor, which furthers an increase in inequality (Claessens and Perotti 2007). Third, both income and wealth are on the rise since the 1990s, with wealth being much more concentrated as wealth can accumulate over time (Jones 2015). According to the 2022 Wealth Inequality Report, in 2021, the richest 10% of the global population takes 52% of global income, whereas the poorest half of the population earns 8.5%. Regarding wealth inequality, the poorest half of the global population possess only 2% of total wealth. By contrast, the richest 10% of the global population own 76% of all wealth.

Finally, inequality and growth are intertwined. While some inequality is necessary and even desirable to reward innovation and risk-taking, excessive income inequality and wealth concentration can hinder economic growth not only by corrupting the political process and distorting economic policies but also by damaging economic opportunities and social mobility and raising sociopolitical instability (Alesina and Rodrik 1994; Galor and Tsiddon 1997; Bagchi and Svejnar 2015). Economic stagnation, according to the Kuznets' curve effect, will result in an increase in inequality (Greenwood and Jovanovic 1990; Barro 2000; Lloyd-Ellis and Bernhardt 2000). Understanding how population aging affects inequality is thus crucial for the policymakers, not least because it provides one possible mechanism for population aging to impact economic growth as well as social welfare.

Theoretically, the consequence of population aging on wealth inequality remains controversial. According to the life-cycle hypothesis of saving, wealth accumulation via saving increases with the age profile before retirement and the wealthy keep saving at high rates. Dispersions in wealth increase also with age as wealth reflects an individual's saving capacity that depends on human capital and skill training which accumulate over the life course. Thus, population aging improves wealth inequality because of a lower proportion of young people with less assets, the so-called demographic effect, but worsens it due to a higher share of older people with unequal

assets, the so-called life-cycle effect. Whether population aging affects wealth inequality is thus an empirical matter. However, the empirical analysis of wealth inequality has limited by data availability, albeit some recent effort has been devoted to mapping both historical and current wealth patterns.

This paper represents the first attempt to provide robust evidence to the nexus between population aging and wealth inequality. The contribution lies in exploring potential nonlinearity between the two variables. Nonlinearity can arise from the fact that mortality declines precede fertility reductions in the process of demographic transition. Population aging is characterized as a decline in the young population share and an increase in the elderly population share (Weil, 1997). Thus, in the early stages of population aging with a decline in fertility corresponding to a drop in mortality, the young-age population share declines and the working-age share increases. This results in lower wealth inequality because of a shift of population away from the young population with less wealth. In the latter stages of population aging, since most of the reduction in the young-age share has already occurred with fertility falling near or even below the replacement rate, the most affected change is in the old-age fraction: an increase in the old-age share and a decline in the working-age share (Bloom et al. 2009). This tends to exacerbate wealth inequality as there is higher fraction of older people with high and unequal wealth. That said, there exists some threshold level of population aging such that the effect of population aging on wealth inequality changes. As such, the investigation helps clarify the theoretical inconclusiveness.

Methodologically, we first consider the dynamic panel system generalized method of moments (GMM) to control for the endogeneity bias. We then appeal to the dynamic panel GMM quantile regression approach to check for differences across countries with different inequality. As the recent upsurge in inequality is driven largely by an increasing concentration of wealth and income at the top end of the distribution, we make use of data on wealth as well as income at the top of the distribution sourced from the World Inequality Database (WID), which provides the most extensive data on the world distribution of income and wealth within and between countries. To provide a broader picture and as a robustness check, we also consider the bottom wealth and income shares. Our GMM estimates indeed suggest significant existence of a population-aging threshold, which tends to be lower for countries with higher wealth inequality according to the quantile estimates.

The remainder of the paper is composed of four sections. Section 2 provides a brief literature review and Sect. 3 describes the data, sets up the basic empirical model and introduces estimation strategies. Section 4 analyzes the empirical results and Sect. 5 concludes the paper.

2 Brief review of literature

The theoretical foundation for population aging to influence income and wealth inequality is the life cycle hypothesis of saving (Modigliani 1966). The theory predicts the level and dispersion of income rise with age. Income tends to be low in young and old age but high in middle age and peak before retirement age.

Moreover, because individuals differ in their human capital and skill building as well as social network, which accumulates over the life course, income is more unequally distributed in old age than in working age. Changes in the population age structure will thus alter the overall distribution of income and income inequality will rise when people get older. Counter arguments exist as well. Old people rely less on income from work and tend to have lower income compared to workers, reducing income inequality. Moreover, if public transfers rooted in social security programs increase the relative income share and the average income of the poorest elderly (Deaton et al. 2002), income inequality may fall. However, if population aging leads to low tax and less generous social security systems (Razin et al. 2002), income inequality can rise with population aging. In Henretta and Campbell (1976), as income before and after retirement is determined by the same factors, income inequality remains stable with age if the redistribution effect of the social security system offsets the accumulated inequality in old age (Hanewald et al. 2021).

While the inheritance plays a significant role in determining wealth, wealth is accumulated via saving and varies also with age (Quadri 1999). According to the life-cycle hypothesis, individuals save to smooth their consumption to maximize their lifetime utility and predicts a hump-shaped pattern of wealth accumulation (saving). Individuals will borrow in young age, save during working years, and dis-save in retirement. If wealth is hump-shaped, accumulated over the working years to finance retirement, then aggregate wealth inequality will decrease with population aging as there are relatively fewer young people who typically own less wealth. Population aging may also lead to higher wealth inequality. While wealth is most concentrated among those who are about to retire, wealth is highly dispersed at retirement, even for people with similar lifetime income (Venti and Wise 1998; Bernheim et al. 2001). Besides, in the presence of precautionary saving and intergenerational transmission of both human capital and bequests, the wealthy not only save more but also keep saving and hold onto large amounts of wealth even when very old (De Nardi 2004; De Nardi et al. 2010; De Nardi and Fella 2017). However, in the buffer-stock model of saving (Deaton 1991), in the presence of liquidity constraints and precautionary saving, consumers accumulate assets as a buffer stock to shield their consumption against income risk. That is, they save if wealth is low (below some target level) but dis-save if wealth is high (above some target level). Thus, population aging has limited effect on wealth inequality.

Empirical work on aging and inequality remains sparse. Most investigations focus income inequality, which has produced mixed results. Some studies find that income is more unequally distributed among the elderly population (Deaton and Paxson 1994; Cameron 2000; Chen et al. 2018). Others show the opposite (Barrett et al. 2000; Prus 2000). Still, several studies find limited distributional consequences of population aging (Bishop et al. 1997; Jantti 1997; Biewen and Juhász 2012). Most of these empirical studies are in a country-specific setting. The estimation results are thus specific to a particular country and fail to generalize to other countries because of substantial differences in cultural norms, institutions, and social welfare programs across countries. To improve along the line, this paper, in a cross-country panel data

setting, tackles the issue by including appropriate control variables as well as country-specific effects.

3 Data and econometric strategy

3.1 Data

Our data consist of 92 developed and developing countries over the period 1995–2020.¹ The coverage of countries and periods are selected simply due to data availability, particularly on wealth inequality. Since changes in demographic structure are low frequency phenomena, we follow the common practice in the empirical macroeconomic literature to average the data over non-overlapping 4-year intervals except for the first and last three years: 1995–1997, 1998–2001, 2002–2005, 2006–2009, 2010–2013, 2014–2017, 2018–2022. This produces at most 7 observations per country for a typical variable in the sample. In so doing, it also reduces measurement errors and the effect of business fluctuations.

As for inequality measures, the Gini index is the most commonly used measure of inequality. It measures the dispersion of income or wealth within a population with higher values indicating less equal income distribution. As it measures only income or wealth dispersion, the Gini coefficient is not a proper indicator of egalitarianism. Like any single summary measure of a set of data, the Gini coefficient cannot tell what is happening to each income or wealth bracket or the absolute income or wealth. The Gini index can rise if some or all income (wealth) brackets experience a rising income (wealth). It is possible that the Gini coefficient falls yet the poor get poorer, and the Gini coefficient rises yet everyone getting richer. Thus, instead of using the Gini index, we consider top 1% and 10% as well as bottom 50% income and wealth shares from the World Inequality Database. The top 1%, 10%, and bottom 50% income share are pre-tax national income shares held by the p99p100, p90p100, and p0p50 group, denoted *top1*, *top10*, and *bot50*, respectively. The top 1%, 10%, and bottom 50% wealth share are net personal wealth shares held by the p99p100, p90p100, and p0p50 group, denoted *topw1*, *topw10*, and *botw50*, respectively. Regarding population aging, we consider old-age population and old-age dependency, i.e., population aged over 64 as a percentage of the total population and working-age population. We also consider life expectancy at birth as a robustness check. These data are sourced from the World Bank's World Development Indicators (WDI) and in natural logarithms.

We include a set of control variables based on the previous literature on the determination of income and wealth inequality. First, we consider GDP per capita growth (*gdpg*) and CPI inflation (*inf*). Berisha and Meszaros (2020) show that both GDP growth and inflation reduce wealth inequality. Economic growth enables poor

¹ Our dataset is available upon request. As for the STATA codes for GMM and GMM quantile estimation procedures as well as panel VAR causality tests, please type “help xtband2”, “help qregpd”, and “help pvar” in STATA.

households to save more out of their earnings, boosting their income and wealth share. Inflation hurts the poor and middle class more than the rich because rich people have better access to finance that enables them to hedge their exposure to inflation (Easterly and Fischer 2001). Next, we include private credit to GDP (*findev*) and trade flows to GDP (*trade*) from WDI. Dabla-Norris et al. (2015) show that rising exposure of sectors to international trade increases the skill intensity and relative demand for skilled labor, contributing to greater inequality. Hasan et al. (2020) find that more efficiency and greater access to finance because of financial development is associated with less wealth inequality. Also added is social benefits to GDP (*benefit*) from IMF's Government Finance Statistics. Anderson et al. (2017) show that social welfare and other social spending are negatively associated with income inequality. Included are political (in)stability (*polstab*) and control of corruption (*ccorrupt*) from the World Bank's World Governance Indicators.² Hasan et al. (2020) demonstrate that political instability, as proxied by the number of wars, tend to increase wealth inequality. Corruption strengthens inequality by facilitating tax evasion and reducing social spending on education or health (Gupta et al. 2002) but weakens inequality in the face of an ineffective bureaucracy (de Vaal and Ebben 2011).

Table A1 in the Appendix lists sample countries and Table A2 reports summary statistics and the correlation matrix. Table A3 presents the panel VAR Granger causality test for population aging and wealth inequality following Abrigo and Love (2016). The results show that (1) population aging variables Granger cause top wealth shares and top wealth shares Granger cause population aging, except life expectancy where two-way Granger causality exists between life expectancy and top wealth shares; (2) bottom wealth shares Granger cause population aging but population aging does not Granger cause bottom wealth shares; and (3) population aging variables Granger cause income shares and income shares Granger cause population aging.

3.2 Econometric strategy

To investigate the effect of population aging (*aging*) on wealth inequality (*y*), we estimate the following dynamic panel model:

$$y_{it} = \rho y_{it-1} + \beta \text{aging}_{it} + \delta CV_{it-1} + \mu_i + e_{it} \quad (1)$$

where subscript *i* and *t* index country and period. *CV* is a set of control variables with one-period lag entering the equation to mitigate potential endogeneity. μ_i is the country-specific effect. e_{it} is the classical error term. y_{it-1} is included to capture potential dynamics and persistence in wealth inequality.

² Political stability measures the likelihood of political instability and/or politically motivated violence, including terrorism. Control of corruption measures the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as capture of the state by elites and private interests.

Table 1 Top 1% wealth share, GMM estimates

	Old-age dependency												
	Old-age population			Old-age population			Old-age population			Old-age population			
	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
Top 1% share _t	1.042*** (0.07)	0.954*** (0.07)	0.954*** (0.05)	0.976*** (0.06)	0.989*** (0.10)	0.886*** (0.21)	0.941*** (0.08)	0.987*** (0.04)	0.965*** (0.07)	0.874*** (0.03)	0.958*** (0.05)	0.978*** (0.04)	
-1													
Old	0.750 (0.68)	-1.759*** (0.59)	-3.135*** (1.12)	-2.231** (0.93)	-4.503*** (1.59)	-4.229** (1.91)	-3.322** (1.35)	-3.437** (1.68)	-3.444** (1.63)	-0.778*** (0.24)	-3.803** (1.62)	-4.047** (1.93)	
Old ²		0.351** (0.17)	0.582** (0.23)	0.409* (0.24)	1.003*** (0.38)	1.067* (0.63)	1.076** (0.53)	0.903** (0.46)	1.196** (0.52)	0.242*** (0.07)	1.497** (0.66)	1.236* (0.66)	
Lifexp							31.973 (250.85)				28.720 (39.89)		
Lifexp ²							-4.240 (30.36)				-3.887 (5.90)		
Young ²								-0.989 (11.01)				6.229 (21.45)	
Young ²								0.214 (1.46)				-0.916 (3.19)	
gdpg _{t-1}	-0.039 (0.06)	-0.036 (0.05)	-0.116* (0.07)	-0.112* (0.06)	-0.089 (0.09)	-0.105 (0.10)	-0.010 (0.09)	-0.038 (0.07)	-0.026 (0.08)	-0.101*** (0.03)	-0.048 (0.08)	-0.046 (0.06)	
Inf _{t-1}			-0.057 (0.09)	-0.051 (0.11)	-0.096 (0.28)	-0.445 (0.29)	-0.286 (0.32)	-0.008 (0.15)	-0.151 (0.24)	-0.557*** (0.06)	-0.341 (0.33)	-0.020 (0.11)	
Findev _{t-1}			0.122 (0.23)	0.369 (0.27)	0.824 (0.92)	-0.802 (0.65)	0.345 (0.44)	0.600* (0.32)	0.490 (0.47)	-0.377*** (0.09)	0.391 (0.36)	0.522 (0.34)	
Trade _{t-1}			-0.142 (0.25)	-0.215 (0.32)	-0.846 (0.63)	0.303 (0.83)	-0.483 (0.63)	-0.683* (0.35)	-0.713** (0.36)	-0.180* (0.10)	-0.373 (0.49)	-0.740** (0.33)	
Polstab _{t-1}				0.240 (0.25)	0.145 (0.30)	-0.568 (0.50)	0.071 (0.33)	0.276 (0.23)	0.084 (0.27)	0.094 (0.12)	-0.034 (0.34)	0.136 (0.27)	
ccorrupt _{t-1}				-0.282 (0.18)	-0.642 (0.71)	-0.672 (0.67)	-0.757 (0.54)	-0.485* (0.25)	-0.728* (0.42)	-0.036 (0.07)	-0.536 (0.36)	-0.413 (0.30)	

Table 1 (continued)

	Old-age population												
	Old-age dependency						Old-age population						
	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
Benefit _{t-1}					0.042 (0.05)	0.859* (0.50)	0.026 (0.06)	0.010 (0.05)	0.025 (0.07)	-0.140*** (0.04)	0.007 (0.06)	0.001 (0.06)	
Constant	-3.092 (3.42)	2.796 (2.80)	5.654* (3.32)	6.194 (4.04)	17.105 (14.23)	9.988* (5.96)	-49.627 (520.31)	8.433 (19.56)	11.060** (5.41)	7.643*** (0.86)	-43.839 (66.95)	-2.589 (34.99)	
Obs	523 (87)	523 (87)	400 (85)	386 (82)	171 (51)	171 (51)	171 (51)	171 (51)	171 (51)	171 (51)	171 (51)	171 (51)	
Instrument count	23	19	20	26	22	17	35	37	26	44	32	41	
Hansen: <i>p</i> -value	0.243	0.386	0.263	0.343	0.578	0.995	0.898	0.982	0.873	0.364	0.953	0.958	
AR(2): <i>p</i> -value	0.0267	0.371	0.247	0.208	0.882	0.113	0.875	0.882	0.881	0.747	0.839	0.844	
$\Delta y/\Delta old=0$ (%)		2.506 12.256	2.693 14.776	2.727 15.287	2.245 9.440	1.982 7.257	1.544 4.683	1.903 6.706	1.440 4.221	1.607 4.990	1.270 3.561	1.637 5.140	

Notes: Period dummies are included in all regressions. Robust standard errors are in parentheses. ****p*<0.01, ***p*<0.05, **p*<0.1

Table 2 Top 1% wealth share, subsamples and quantile estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(3)	(4)	(5)	(6)
	GMM											
	cap	cca	lac	mena	na	sa	ssa	Quantile	25	50	75	90
top 1% share _{t-1}	0.966*** (0.10)	1.054*** (0.04)	0.879*** (0.08)	0.977*** (0.03)	1.015*** (0.08)	1.031*** (0.06)	0.968*** (0.10)	0.838*** (0.013)	0.947*** (0.011)	0.935*** (0.021)	0.980*** (0.010)	0.993*** (0.019)
olddep	-4.362** (1.83)	-3.947** (1.97)	-3.581** (1.51)	-4.563** (2.24)	-3.280** (1.46)	-3.241** (1.45)	-3.600** (1.63)	-4.208*** (0.378)	-5.793*** (0.723)	-2.698** (1.211)	-2.000** (0.936)	-1.962*** (0.689)
olddep ²	0.831* (0.45)	0.965* (0.52)	0.789*** (0.40)	0.908* (0.48)	0.798* (0.41)	0.779*** (0.37)	1.037*** (0.40)	0.878*** (0.106)	1.137*** (0.169)	0.484*** (0.238)	0.588*** (0.211)	0.885*** (0.131)
gdpg _{t-1}	-0.096 (0.10)	0.039 (0.07)	-0.059 (0.10)	-0.017 (0.05)	-0.059 (0.09)	-0.085 (0.09)	-0.052 (0.09)	-0.001 (0.022)	-0.211*** (0.073)	-0.085* (0.045)	0.022 (0.022)	0.164* (0.085)
inf _{t-1}	0.080 (0.26)	0.010 (0.22)	-0.178 (0.28)	0.143 (0.15)	-0.130 (0.29)	-0.016 (0.22)	-0.269 (0.30)	0.273*** (0.079)	0.112 (0.099)	-0.098 (0.188)	-0.417*** (0.152)	0.321 (0.387)
findev _{t-1}	1.241 (0.77)	0.947 (0.59)	0.490 (0.47)	0.889*** (0.25)	0.346 (0.47)	0.579 (0.63)	-0.088 (0.75)	0.385*** (0.165)	0.040 (0.193)	-0.260*** (0.130)	-0.080 (0.141)	-0.051 (0.147)
trade _{t-1}	-1.127* (0.64)	-0.758** (0.36)	-0.439 (0.45)	-0.901*** (0.23)	-0.690 (0.45)	-0.617 (0.47)	-0.239 (0.43)	0.491** (0.208)	0.488** (0.201)	0.138 (0.256)	-0.020 (0.077)	0.187 (0.387)
polstab _{t-1}	0.170 (0.37)	-0.045 (0.31)	-0.118 (0.31)	0.618*** (0.14)	0.291 (0.35)	0.548 (0.35)	-0.051 (0.36)	0.202** (0.086)	-0.032 (0.142)	0.153*** (0.056)	-0.010 (0.023)	-0.198*** (0.056)
ccorrupt _{t-1}	-0.782 (0.73)	-0.614 (0.62)	-0.365 (0.40)	-0.769*** (0.23)	-0.299 (0.40)	-0.506 (0.46)	-0.481 (0.44)	0.387*** (0.108)	0.499*** (0.160)	0.162* (0.087)	0.012 (0.060)	-0.396** (0.189)
benefit _{t-1}	0.050 (0.07)	0.031 (0.06)	-0.003 (0.07)	0.124 (0.10)	0.025 (0.05)	0.045 (0.06)	0.083 (0.08)	-0.170** (0.069)	-0.009 (0.024)	0.108 (0.112)	0.131* (0.080)	-0.067 (0.203)
Constant	23.156** (10.00)	13.750 (13.48)	12.461**	7.883***	7.644	8.100	6.192					
Obs	148(44)	135(37)	143(43)	133(41)	165(50)	159(48)	143(43)	171(51)	171(51)	171(51)	171(51)	171(51)
instrument count	22	22	22	36	23	24	24					
Hansen J:	0.635	0.862	0.908	0.570	0.592	0.724	0.786					
p-value												

Table 2 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(1)	(3)	(4)	(5)	(6)
GMM								Quantile				
cap	0.186	0.223	0.102	0.535	0.232	0.260	0.370	10	25	50	75	90
AR(2):												
p-value												
$\Delta y / \Delta \text{old} = 0$	2.625	2.045	2.269	2.513	2.055	2.080	1.736	2.396	2.550	2.787	1.701	1.108
(%)	13.805	7.729	9.670	12.338	7.807	8.004	5.675	10.98	12.80	16.232	5.479	3.028

The dependent variable is the top 1% wealth share. eap = East Asia & Pacific, eca = Europe & Central Asia, lac = Latin America & Caribbean, mena = Middle East & North Africa, na = North America, sa = South Asia, and ssa = Sub-Saharan Africa. For (1)–(7), each region is excluded one at a time from the sample. Period dummies are included. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3 Top 10% wealth share, GMM estimates

	Old-age dependency											
	Old-age population						Old-age population					
	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Top 10% Share _{t-1}	0.992*** (0.05)	0.938*** (0.07)	0.995*** (0.06)	0.975*** (0.06)	0.953*** (0.06)	0.965*** (0.15)	0.928*** (0.05)	0.961*** (0.06)	0.933*** (0.06)	1.099*** (0.11)	0.938*** (0.09)	0.970*** (0.05)
Old	0.366 (0.71)	-1.482** (0.62)	-2.433* (1.27)	-2.282** (1.13)	-2.364*** (0.79)	-3.359** (1.50)	-2.989** (1.31)	-3.590** (1.71)	-2.909*** (1.01)	-1.531*** (0.30)	-4.347** (2.06)	-2.942* (1.57)
Old ²		0.320** (0.15)	0.567** (0.29)	0.510** (0.25)	0.544** (0.25)	0.806** (0.41)	0.861* (0.47)	0.845** (0.41)	0.874*** (0.32)	0.468** (0.37)	1.312** (0.66)	0.846* (0.49)
Lifexp							23.880 (240.18)				131.399 (384.09)	
Lifexp ²							-2.949 (28.99)				-15.353 (46.28)	
Young								1.249 (9.21)				-7.655 (15.20)
Young ²								-0.166 (1.27)				1.117 (2.33)
gdpgrt _{t-1}	-0.012 (0.07)	-0.044 (0.05)	-0.087 (0.07)	-0.087 (0.07)	-0.041 (0.06)	-0.089 (0.09)	-0.036 (0.07)	-0.053 (0.06)	-0.059 (0.09)	-0.099 (0.08)	-0.070 (0.08)	-0.061 (0.05)
Inf _{t-1}			0.053 (0.09)	0.034 (0.12)	0.126 (0.10)	-0.179 (0.36)	-0.030 (0.28)	0.058 (0.17)	0.064 (0.24)	-0.369 (0.27)	-0.087 (0.30)	0.055 (0.18)
Findev _{t-1}			0.037 (0.16)	0.300 (0.23)	0.583** (0.25)	-0.289 (0.71)	0.334 (0.34)	0.530 (0.38)	0.593 (0.44)	-0.452 (0.45)	0.397 (0.42)	0.584* (0.33)
Trade _{t-1}			-0.142 (0.26)	-0.265 (0.30)	-0.660* (0.36)	-0.121 (0.68)	-0.342 (0.54)	-0.577* (0.35)	-0.639* (0.38)	-0.180 (0.51)	-0.568 (0.51)	-0.561* (0.33)

Table 3 (continued)

	Old-age dependency														
	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Income	Wealth	Wealth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)			
Polstab _{t-1}				0.197 (0.19)	0.351 (0.25)	-0.270 (0.42)	0.210 (0.32)	0.174 (0.24)	0.230 (0.28)	0.182 (0.32)	-0.043 (0.34)	0.129 (0.22)			
ccorrupt _{t-1}				-0.369** (0.16)	-0.523** (0.25)	-0.533 (0.54)	-0.606* (0.33)	-0.461 (0.29)	-0.660** (0.30)	0.028 (0.34)	-0.581 (0.50)	-0.461 (0.28)			
Benefit _{t-1}					0.018 (0.03)	0.577 (0.38)	0.012 (0.03)	0.004 (0.05)	0.022 (0.04)	-0.088 (0.06)	0.005 (0.05)	0.008 (0.05)			
Constant	-0.635 (3.95)	5.231 (5.12)	2.635 (4.54)	9.619* (5.29)	9.234 (6.07)	11.588 (8.83)	-36.785 (496.92)	8.861 (16.11)	13.845** (6.89)	2.513 (5.66)	-265.797 (800.72)	23.176 (24.49)			
Obs	529(88)	529(88)	404(86)	341(79)	171(51)	171(51)	171(51)	171(51)	171(51)	171(51)	171(51)	171(51)			
Instrument count	22	20	22	21	29	19	35	32	26	18	28	33			
Hansen: <i>p</i> -value	0.124	0.503	0.277	0.374	0.934	0.553	0.940	0.912	0.867	0.851	0.843	0.949			
AR(2): <i>p</i> -value	0.287	0.108	0.146	0.303	0.226	0.167	0.178	0.108	0.267	0.253	0.109	0.188			
Δy		2.316	2.146	2.237	2.173	2.084	1.736	2.124	1.664	1.636	1.657	1.739			
$\Delta \text{old} = 0$		10.135	8.551	9.365	8.785	8.037	5.675	8.365	5.280	5.114	5.244	5.692			

Period dummies are included in all regressions. Robust standard errors are in parentheses. ****p* < 0.01, ***p* < 0.05, **p* < 0.1

To explore potential nonlinearity, we then add the quadratic term of population aging into Eq. (1):

$$y_{it} = \rho y_{it-1} + \beta_1 \text{aging}_{it} + \beta_2 \text{aging}_{it}^2 + \delta CV_{it-1} + \mu_i + e_{it} \quad (2)$$

We expect that $\beta_1 > 0$ and $\beta_2 < 0$, meaning that wealth inequality follows an inverted-U with population aging. However, if $\beta_1 < 0$ and $\beta_2 > 0$, then wealth inequality follows a U with population aging. The associated threshold of population aging is $-\beta_1/2\beta_2$.

The above equations are subject to econometric shortcomings. The first is related to dynamics due to the inclusion of one-period lagged dependent variable, which introduces autocorrelation. The second is about omitted-variables effects. Both population aging and inequality are highly policy-relevant and thus may be driven by government preferences. The last one concerns reverse causation. Rising inequality may bring about higher fertility rates since the poor tend to have more children (Perotti 1996). The preferred estimator is a dynamic panel system GMM proposed by Arellano and Bover (1995) and Blundell and Bond (1998). The approach mitigates the endogeneity bias due to dynamics, reverse causality and omitted variables using internal instruments. Specifically, in the system including both the first-difference and level equations, the GMM estimator instruments the first-difference equation with lagged independent variables but uses lagged differenced independent variables as instruments for the level equation. Thus, the consistency of GMM estimator depends on the absence of second-order autocorrelation in the error term and correlation between instruments and the error term. We then apply two model specification tests: the Arellano–Bond AR(2) test for the null of no second-order autocorrelation and the Hansen J test for the null of valid overidentifying restrictions. Besides, in case of a small sample size, we consider Windmeijer’s corrected standard errors to mitigate the small sample bias. To preserve efficiency, we limit the number of the lags for instruments and collapse the instrument sets.

The GMM approach assumes for parameter homogeneity and estimates the population aging effect on the mean of the wealth inequality distribution. From a policy perspective, however, it is more interesting to know the consequence of population aging on wealth inequality in regimes with low and high wealth inequality, i.e., whether the population aging effect is robust across regimes with different wealth inequality. We then consider the dynamic panel GMM quantile model with non-additive fixed effects advanced by Powell (2022) to explore how population aging affects wealth inequality at different quantiles of the conditional wealth inequality distribution. This approach produces estimates of the conditional distribution of wealth inequality. Instead of providing estimates of the conditional distribution of wealth inequality relative to fixed effect as the quantile estimators with additive fixed effects, the approach includes the fixed effects in the error term and then estimates the panel quantile regression via the GMM estimator to overcome the endogeneity bias. Please refer to Powell (2022) for detailed discussions.

Specifically, we estimate the conditional quantile function for quantile q as follows:

$$Q_{y_{it}}(q|x_{it}) = b_{1q}y_{it-1} + b_{2q}aging_{it} + b_{3q}aging_{it}^2 + b_{4q}CV_{it-1} \quad (3)$$

where $x = (y_{it-1}, aging_{it}, aging_{it}^2, CV_{it-1})'$. It is noted that $b_{\tau q}$ measures the marginal effect of the τ th explanatory variable on wealth inequality at the q^{th} (such as the 10th, 30th, 50th, 70th, and 90th) quantile. For estimation, lagged explanatory variables are used as instruments.

4 Empirical results

Table 1 reports the benchmark estimation results for the top 1% wealth share using old-age dependency. We first note that all models, also in other tables, are properly specified. Both specification tests fail to reject the null of no second-order serial correlation and the validity of instruments. Moreover, the number of instruments is less than the number of cross-section units. It is also observed that the one-period lagged top 1% wealth (and income) share is positive and statistically significant, suggesting persistence in the wealth (and income) share.

Turn to the estimates. Column (1) reports the linear effect. Old-age dependency has a positive but not significant effect on the top 1% wealth share. However, when adding the quadratic term of old-age dependency in Column (2), we find that old-age dependency becomes negative and significant, and its square is significantly positive. The top 1% wealth share follows a U path, i.e., decreases and then increases when old-age dependency rises, with a threshold level of old-age dependency occurring at 2.506 (equivalent to 12.26%). The evidence is robust to controlling for economic variables, political factors, and social benefits, respectively, in Columns (3)–(5), with an old-age dependency threshold ranging from 2.34 (about 10.33%) to 2.72 (about 15.18%). It is also found that the top 1% income share has a U shape along with population aging as shown in Column (6). Columns (7) and (8) examine whether life expectancy and young-age dependency matter and show a minor role for them to play. The remaining Columns of Table 1 confirm the above findings using the old-age population ratio. The threshold level of old-age population ratio for the top 1% wealth share to increase ranges from 1.27 (3.56%) to 1.64 (5.14%) and that for top 1% income share to increase is 1.61 (4.99%).

For illustration, in Fig. 1, we plot the relationship of old-age dependency with the top 1% wealth and income share that correspond to Columns (5) and (6) of Table 1.³ The top left panel documents a U-shaped pattern between old-age dependency and the top 1% wealth share conditional on all control variables. Moreover, the estimated minimum value of the top 1% wealth share is 0.33% when the threshold level of old-age dependency is 2.25 (9.44%) such that an increase or decrease in old-age dependency will lead to an increase in the top 1% wealth share. The bottom left panel plots the marginal effects along the entire distribution of top 1% wealth share. Following the U-shaped pattern, the marginal effect on the top 1% wealth share is negative in a

³ The marginal effects and standard errors are calculated through the delta method, based on the sample mean of variables in the regression.

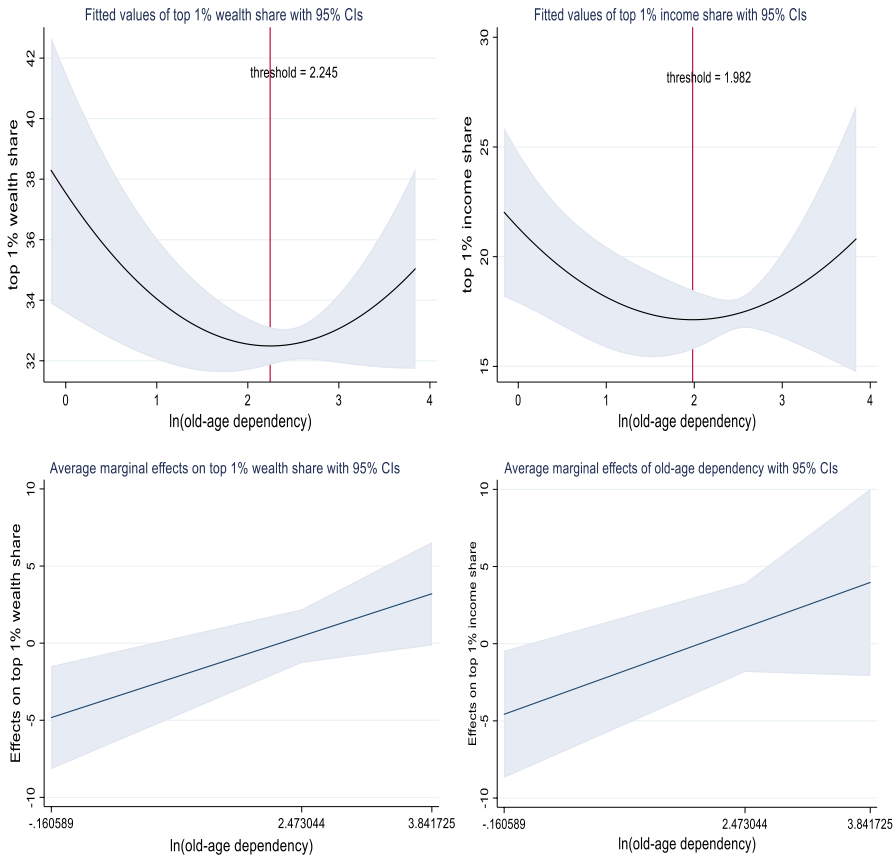


Fig. 1 Top 1% wealth and income share, Columns (5) and (6) of Table 1

less aging society but positive in a more aging society. More specifically, the respective derivative of top 1% wealth share with respect to old-age dependency is -4.83, 0.46, and 3.20 when old-age dependency is at its minimum, mean, and maximum. Similarly, for the top 1% income share shown in the right two panels, the minimum level of top 1% income share is 0.17% when the threshold level is 1.98 (7.26%). At the minimum, mean, and maximum level of old-age dependency, the respective derivative of top 1% income share with respect to old-age dependency is -4.57, 1.05, and 3.97. A one-percent increase in old-age dependency at the minimum, mean, and maximum level will cause the top 1% wealth (income) share to decrease by 4.83% (4.57%) but increase by 0.46% (1.05%) and 3.20% (3.97%).

Table 2 checks for regional and quantile effects using old-age dependency with full controls. The first seven columns examine whether our results are affected by any region. Toward the end, East Asia and Pacific (*eap*), Europe and Central Asia (*eca*), Latin America and Caribbean (*lac*), Middle East and North Africa (*mena*), North America (*na*), South Asia (*sa*), and Sub-Saharan Africa (*ssa*) are excluded one

at a time from the baseline sample. There appears little influence on the U link of the top 1% wealth share with old-age dependency, albeit the significant level drops to the 10% level for some cases. The old-age dependency threshold level ranges between 1.74 (5.68%) and 2.63 (13.81%). The quantile estimates in the last six columns further show that our results are robust to outliers and parameter heterogeneity. The U link between the top 1% wealth share and old-age dependency is observed across the conditional distribution of the top 1% wealth share. Despite so, the inflection point of the U curve appears much lower at upper than lower quantiles. Countries with high wealth inequality will experience a rise in their wealth inequality (i.e., high top 1% wealth share) at much lower levels of old-age dependency.

Tables 3 and 4 experiment with the top 10% wealth and income share. In Table 3, across different model specifications, population aging proxied by old-age dependency or population ratios has a U effect on the top 10% wealth and income share. For illustration, Fig. 2 depicts the relationship of old-age dependency with the top 10% wealth and income share based on Columns (5) and (6) of Table 3. The top panels document a U-shaped relationship. Moreover, the respective threshold occurs at 2.17 (8.79%) and 2.08 (8.04%) with the predicted maximum level of top 10% wealth and income share 0.65% and 0.47% such that an increase or decrease in old-age dependency will lead to a rise in wealth and income inequality. The bottom panels plot the marginal effects along the entire distribution of top 10% wealth and income share. The marginal effect is negative in a less aging society but positive in a more aging society, following the U-shaped pattern. Specifically, at the minimum, mean, and maximum level of old-age dependency, the respective derivative of top 1% wealth (income) share with respect to old-age dependency is -2.54 (-3.61), 0.33 (0.63), and 1.82 (2.83). A one-percent increase in old-age dependency at the minimum, mean, and maximum level will cause the top 10% wealth (income) share to decrease by 2.54% (3.61%) and 0.33% (0.63%) but increase by 1.82% (2.83%).

In Table 4, we first observe that a U-curve link is not driven by any specific regions. The old-age dependency threshold level for the top 10% wealth share to rise ranges from 1.62 (5.03%) to 2.18 (8.84%). We next find that the U link between the top 10% wealth share and old-age dependency holds also across the conditional distribution of the top 1% wealth share. Nonetheless, the threshold level of old age dependency seems much lower at upper than lower quantiles. Countries with high wealth inequality (i.e., high top 10% wealth share) will have an increase in their wealth inequality at much lower levels of old-age dependency.

So far, our evidence suggests that population aging above a certain threshold will benefit the very wealthy, widening the gap between the wealthy and the poor. It is not clear whether in the process the poor get hurt, however. Thus, Tables 5 and 6 experiment with the bottom 50% wealth and income share. In Table 5, across regressions with different controls, the bottom 50% wealth and income share follow an inverted U-shaped process, i.e., first rise and then decline, with increased old-age dependency and population ratios. Figure 3 elucidates the relationship of old-age dependency with the bottom 50% wealth and income share based on Columns (5) and (6) of Table 5. The top panels document a hump-shaped relationship. Moreover, the respective threshold occurs at 2.65 (14.20%) and 1.94 (6.95%) with the predicted maximum level of bottom 50% wealth and income share 3.8% and 14% in

Table 4 Top 10% wealth share, subsamples and quantile estimates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	Quantile			(10)	(11)	(12)
	GMIM	eca	lac	mena	na	sa	ssa	10	25	50	75	90	
Top 10% share _{t-1}	1.037*** (0.10)	1.037*** (0.09)	0.974*** (0.06)	1.002*** (0.03)	0.967*** (0.07)	0.966*** (0.07)	0.912*** (0.06)	0.873*** (0.025)	0.935*** (0.009)	0.932*** (0.010)	0.968*** (0.007)	0.936*** (0.021)	
Olddep	-2.298** (1.03)	-3.091** (1.43)	-1.528** (0.75)	-4.166** (2.16)	-2.193*** (0.80)	-2.384*** (0.69)	-3.103** (1.24)	-1.775*** (0.652)	-2.637*** (0.477)	-0.954*** (0.283)	-1.697*** (0.199)	-1.764** (0.829)	
Olddep ²	0.598** (0.29)	0.787** (0.38)	0.473* (0.25)	1.019** (0.43)	0.531** (0.24)	0.547** (0.22)	0.864** (0.37)	0.337** (0.163)	0.474*** (0.076)	0.195** (0.076)	0.607*** (0.058)	0.521*** (0.199)	
gdpgtr _{t-1}	-0.063 (0.06)	-0.041 (0.10)	0.059 (0.07)	-0.050 (0.05)	-0.029 (0.06)	-0.061 (0.05)	-0.061 (0.06)	0.096*** (0.034)	-0.002 (0.087)	-0.057** (0.025)	-0.013 (0.035)	-0.003 (0.063)	
Inf _{t-1}	0.133 (0.18)	0.330 (0.24)	-0.019 (0.28)	-0.278 (0.18)	0.127 (0.14)	0.141 (0.09)	-0.214 (0.22)	0.809** (0.324)	0.141 (0.480)	-0.262*** (0.077)	0.119*** (0.034)	-1.341*** (0.207)	
Findev _{t-1}	-0.044 (0.37)	0.906 (0.62)	0.323 (0.43)	0.107 (0.24)	0.589* (0.30)	0.615** (0.24)	0.047 (0.40)	0.954*** (0.223)	0.089 (0.493)	-0.178** (0.084)	-0.074 (0.045)	0.323** (0.127)	
Trade _{t-1}	-0.600 (0.39)	-0.416 (0.51)	-0.229 (0.39)	-0.560*** (0.22)	-0.623* (0.38)	-0.635* (0.38)	-0.305 (0.36)	0.429*** (0.121)	0.329** (0.135)	0.206* (0.118)	-0.298*** (0.049)	-1.140*** (0.301)	
Polstab _{t-1}	0.231 (0.36)	0.134 (0.46)	0.176 (0.24)	0.397*** (0.14)	0.399 (0.27)	0.438*** (0.17)	-0.104 (0.25)	0.021 (0.019)	0.055*** (0.017)	-0.181 (0.123)	0.398*** (0.124)	0.061** (0.028)	
ccorrupt _{t-1}	0.043 (0.50)	-0.617 (0.64)	-0.467* (0.26)	-0.535*** (0.13)	-0.545** (0.24)	-0.550** (0.26)	-0.456* (0.27)	0.724*** (0.187)	0.177 (0.132)	0.100 (0.070)	-0.049 (0.031)	-0.410*** (0.107)	
Benefit _{t-1}	0.050 (0.05)	0.014 (0.07)	-0.002 (0.04)	-0.033 (0.03)	0.016 (0.04)	0.013 (0.03)	0.037 (0.05)	1.160*** (0.281)	0.245** (0.110)	0.112*** (0.019)	-0.033*** (0.009)	-1.122*** (0.169)	
Constant	-1.465 (10.47)	6.730 (9.70)	6.762 (5.34)	10.388*** (3.96)	8.014 (5.86)	8.512 (7.16)	13.049** (6.60)						
Obs	148(44)	135(37)	143(43)	133(41)	165(50)	159(48)	143(43)	171(51)	171(51)	171(51)	171(51)	171(51)	

Table 4 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Quantile											
	GMM											
	eap	eca	lac	mena	na	sa	ssa	10	25	50	75	90
Instrument count	25	26	30	30	28	29	27					
Hansen J:	0.852	0.739	0.529	0.411	0.909	0.975	0.772					
P-value												
AR(2): p-value	0.101	0.143	0.308	0.390	0.141	0.176	0.324					
$\Delta y/\Delta \alpha/d=0$	1.921	1.964	1.615	2.044	2.065	2.179	1.796	2.634	2.782	2.446	1.397	1.693
(%)	6.828	7.128	5.028	7.723	7.885	8.837	6.025	13.929	16.151	11.542	4.044	5.436

The dependent variable is the top 10% wealth share. Period dummies are included. eap = East Asia & Pacific, eca = Europe & Central Asia, lac = Latin America & Caribbean, mena = Middle East & North Africa, na = North America, sa = South Asia, and ssa = Sub-Saharan Africa. For (1)-(7), each region is excluded one at a time from the sample. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

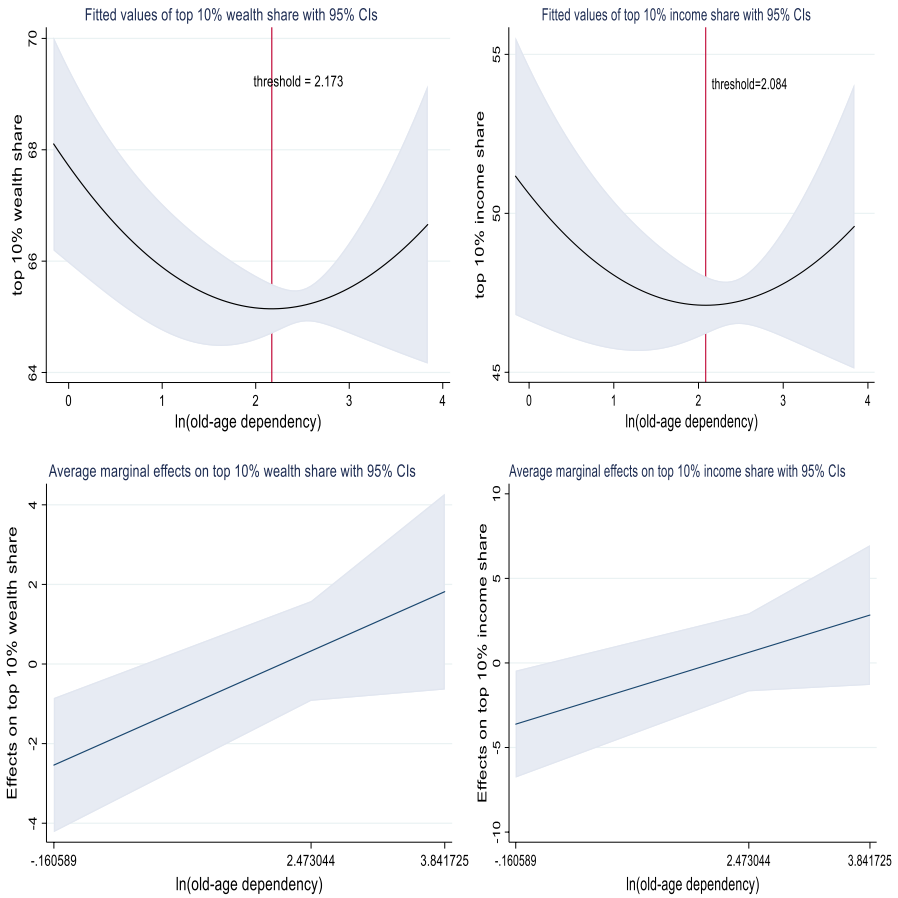


Fig. 2 Top 10% wealth and income share, Columns (5) and (6) of Table 3

the sense that any deviation from the threshold level of old-age dependency will lead to a fall in bottom 50% wealth and income shares. The bottom panels plot the marginal effects along the entire distribution of bottom 50% wealth and income share. The marginal effect is positive in a less aging society but negative in a more aging society, following the hump-shaped pattern. Specifically, at the minimum, mean, and maximum level of old-age dependency, the respective derivative of bottom 50% wealth (income) share with respect to old-age dependency is 1.05 (1.72), 0.07 (-0.44), and -0.44 (-1.56). Table 6 further shows that an inverted U-curve link is not caused by any specific regions and holds across different levels of the bottom 50% wealth share. Besides, the inflection point of the inverted-U curve increases with quantiles. Countries with high wealth inequality (i.e., low bottom 50% wealth share) will experience a rise in their wealth inequality at much lower levels of old-age dependency.

Table 5 Bottom 50% wealth share

	Old-age dependency												
	Old-age dependency						Old-age population						
	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	
Bottom 50% share _{t-1}	0.760*** (0.11)	0.922*** (0.10)	0.867*** (0.05)	0.910*** (0.12)	0.937*** (0.12)	0.898*** (0.27)	0.881*** (0.13)	0.957*** (0.07)	0.943*** (0.12)	0.930*** (0.10)	0.947*** (0.13)	0.973*** (0.08)	
Old	0.308 (0.27)	0.479*** (0.15)	0.700*** (0.27)	0.714* (0.42)	0.987** (0.49)	1.591*** (0.53)	1.409** (0.68)	2.818** (2.43)	0.994*** (0.49)	0.236* (1.01)	1.348** (0.60)	6.016** (4.38)	
Old ²		-0.106** (0.05)	-0.158*** (0.06)	-0.185* (0.10)	-0.186** (0.07)	-0.410* (0.253)	-0.373** (0.18)	-0.569** (0.33)	-0.279** (0.11)	-0.071** (0.30)	-0.436** (0.20)	-1.360** (0.66)	
Lifexp							-69.987 (72.20)				-111.874 (108.48)		
Lifexp ²							8.574 (8.70)				13.411 (13.06)		
Young								0.170 (0.45)				-0.178 (0.49)	
Young ²								-0.013 (0.11)				0.094 (0.15)	
gdpg _{t-1}	0.021 (0.01)	0.021* (0.01)	0.034* (0.02)	0.032 (0.02)	0.012 (0.02)	0.028 (0.04)	-0.004 (0.02)	0.006 (0.02)	0.005 (0.02)	0.030 (0.05)	-0.014 (0.04)	0.002 (0.02)	
Inf _{t-1}			-0.020 (0.04)	-0.005 (0.05)	-0.052 (0.06)	0.178 (0.31)	0.028 (0.04)	-0.053 (0.04)	-0.021 (0.06)	0.084 (0.16)	0.039 (0.10)	-0.082 (0.05)	
Findev _{t-1}			-0.021 (0.06)	-0.138 (0.10)	-0.251 (0.16)	0.468 (0.62)	-0.253 (0.18)	-0.261** (0.11)	-0.223 (0.16)	0.170 (0.33)	-0.202 (0.13)	-0.205 (0.14)	
Trade _{t-1}			0.077 (0.09)	0.144 (0.15)	0.211* (0.13)	-0.081 (0.35)	0.144 (0.18)	0.196** (0.10)	0.154 (0.13)	0.094 (0.37)	0.104 (0.18)	0.169 (0.13)	
Polstab _{t-1}			-0.137 (0.27)	-0.137 (0.24)	-0.074 (0.06)	0.161 (0.50)	-0.011 (0.09)	-0.096 (0.09)	-0.060 (0.09)	-0.071 (0.22)	0.067 (0.12)	-0.127 (0.13)	
ccorrupt _{t-1}			0.243 (0.25)	0.243 (0.25)	0.163* (0.09)	0.313 (0.53)	0.150 (0.10)	0.124** (0.06)	0.188 (0.15)	0.081 (0.33)	0.096 (0.13)	0.097 (0.06)	

Table 5 (continued)

	Old-age dependency				Old-age population							
	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth	Wealth
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Benefit _{t-1}					-0.015 (0.01)	-0.320 (0.56)	-0.024 (0.02)	-0.011 (0.06)	-0.013 (0.01)	0.012 (0.23)	-0.016 (0.01)	-0.018 (0.01)
Constant	0.522 (0.46)	-0.060 (0.37)	-0.105 (0.65)	-1.662 (1.64)	-3.250 (2.37)	-2.157 (1.86)	139.859 (149.83)	-10.459** (4.50)	-2.993 (2.74)	-1.408 (1.45)	230.555 (226.04)	-15.188** (7.22)
Obs	529(88)	529(88)	355(83)	341(79)	171(51)	171(51)	171(51)	171(51)	171(51)	171(51)	171(51)	171(51)
instrument count	23	19	25	24	30	18	32	31	28	19	29	30
Hansen: <i>p</i> -value	0.112	0.776	0.779	0.563	0.667	0.571	0.810	0.888	0.525	0.655	0.833	0.674
AR(2): <i>p</i> -value	0.381	0.204	0.643	0.302	0.187	0.127	0.177	0.186	0.179	0.417	0.216	0.182
$\Delta y/\Delta old = 0$		2.259	2.215	1.930	2.653	1.939	1.889	2.476	1.781	1.656	1.546	2.212
(%)		9.574	9.161	6.890	14.197	6.952	6.613	11.897	5.936	5.234	4.693	9.132

Period dummies are included in all regressions. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6 Bottom 50% wealth share, subsamples and quantile estimates

	Quantile											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GMM												
cap		eca	lac	mena	na	sa	ssa	10	25	50	75	90
Bottom 50	1.003*** (0.08)	0.961*** (0.10)	0.983*** (0.04)	1.045*** (0.03)	0.941*** (0.13)	0.955*** (0.08)	0.923*** (0.09)	0.928*** (0.012)	0.959*** (0.008)	0.951*** (0.020)	0.842*** (0.012)	0.812*** (0.028)
Olddep	0.437** (0.18)	1.167*** (0.45)	0.450** (0.21)	1.644*** (0.56)	1.349*** (0.47)	0.874*** (0.38)	0.906*** (0.34)	0.518*** (0.196)	0.594*** (0.074)	0.929*** (0.377)	2.863*** (0.270)	0.672*** (0.250)
Olddep ²	-0.106* (0.06)	-0.250*** (0.09)	-0.156*** (0.06)	-0.381*** (0.11)	-0.289*** (0.10)	-0.161*** (0.06)	-0.261*** (0.12)	-0.188*** (0.050)	-0.172*** (0.019)	-0.220*** (0.092)	-0.641*** (0.067)	-0.141*** (0.039)
gdppgr _{t-1}	0.000 (0.01)	0.033 (0.03)	-0.025 (0.02)	-0.028* (0.02)	0.022 (0.03)	0.010 (0.02)	-0.006 (0.02)	-0.025** (0.012)	0.006 (0.007)	-0.004 (0.013)	-0.034*** (0.010)	-0.032*** (0.010)
Inf _{t-1}	-0.067** (0.03)	-0.097* (0.06)	0.030 (0.05)	-0.054 (0.04)	0.002 (0.08)	-0.053 (0.07)	0.055 (0.06)	0.183*** (0.033)	0.186*** (0.040)	-0.147* (0.088)	-0.146 (0.138)	-0.045 (0.054)
Findev _{t-1}	-0.074 (0.07)	-0.299*** (0.14)	0.036 (0.12)	-0.189*** (0.05)	-0.332 (0.23)	-0.240* (0.14)	-0.046 (0.14)	0.056 (0.044)	-0.053*** (0.017)	0.043 (0.075)	0.150*** (0.053)	-0.111 (0.110)
Trade _{t-1}	0.119 (0.13)	0.147 (0.13)	0.002 (0.11)	0.117** (0.05)	0.218 (0.16)	0.217 (0.15)	0.101 (0.15)	-0.080** (0.037)	-0.092** (0.045)	-0.024 (0.036)	0.021 (0.025)	0.057 (0.079)
polstab _{t-1}	-0.037 (0.08)	-0.082 (0.08)	-0.009 (0.08)	-0.097** (0.04)	-0.071 (0.11)	-0.125** (0.06)	0.042 (0.08)	-0.043*** (0.004)	-0.009** (0.005)	-0.008 (0.013)	-0.027*** (0.009)	-0.013 (0.017)
ccorrupt _{t-1}	0.009 (0.08)	0.264* (0.14)	0.060 (0.07)	0.175*** (0.03)	0.310* (0.18)	0.176** (0.08)	0.101 (0.06)	0.174*** (0.027)	0.141*** (0.013)	-0.061 (0.057)	-0.050* (0.027)	0.001 (0.053)
Benefit _{t-1}	-0.014 (0.01)	-0.018 (0.01)	-0.010 (0.01)	-0.005 (0.01)	-0.012 (0.02)	-0.013 (0.01)	-0.012 (0.02)	-0.089*** (0.023)	-0.014 (0.026)	-0.066* (0.038)	-0.318*** (0.052)	-0.050 (0.038)
Constant	0.194 (0.88)	-4.483** (1.91)	0.183 (1.18)	-2.058*** (0.75)	-6.258* (3.66)	-2.976 (1.94)	-1.645 (1.32)					
Obs	148(44)	135(37)	143(43)	133(41)	165(50)	159(48)	143(43)	171(51)	171(51)	171(51)	171(51)	171(51)
Instrument count	27	28	30	30	26	30	30					
Hansen: p-value	0.944	0.837	0.796	0.807	0.668	0.789	0.587					

Table 6 (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	Quantile				(12)
	cap	eca	lac	mena	na	sa	ssa	10	25	50	75	90
AR(2):	0.179	0.262	0.151	0.151	0.211	0.211	0.225					
<i>p</i> -value												
$\Delta y/\Delta old=0$	2.061	2.334	1.442	2.157	2.334	2.714	1.736	1.378	1.727	2.111	2.233	2.383
(%)	7.854	10.319	4.229	8.645	10.319	15.090	5.675	3.967	5.624	8.256	9.328	10.837

The dependent variable is the bottom 50% wealth share. Period dummies are included. eap = East Asia & Pacific, eca = Europe & Central Asia, lac = Latin America & Caribbean, mena = Middle East & North Africa, na = North America, sa = South Asia, and ssa = Sub-Saharan Africa. For (1)–(7), each region is excluded one at a time from the sample. Robust standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

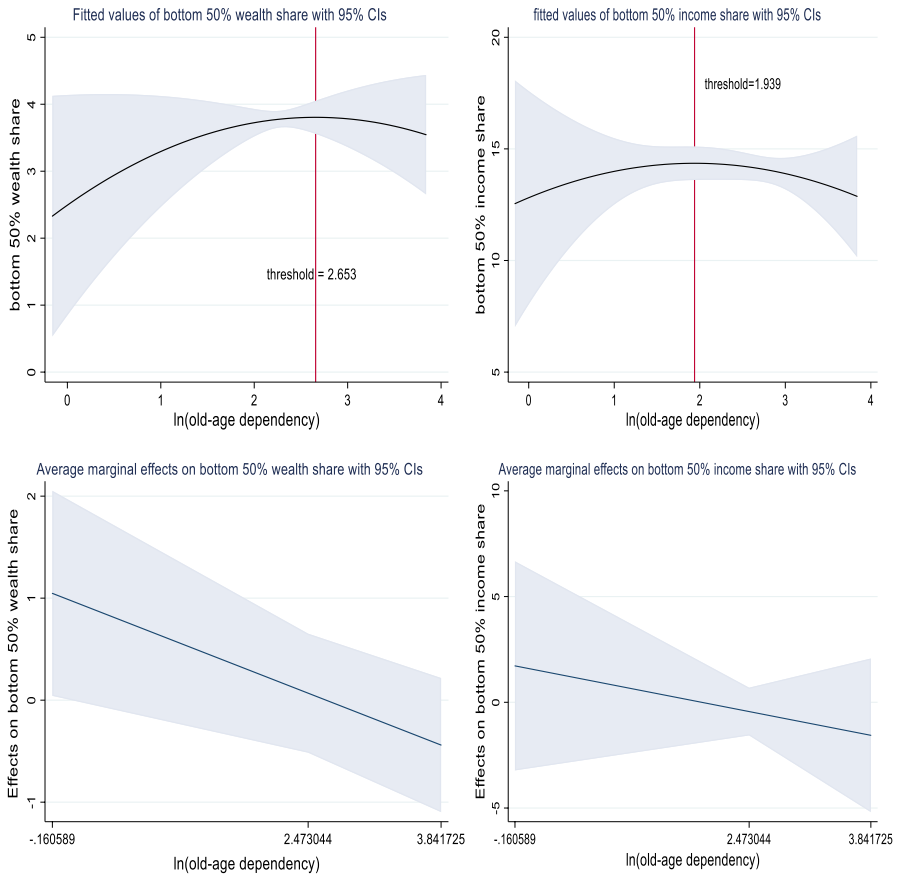


Fig. 3 Bottom 50% wealth and income share, Columns (5) and (6) of Table 5

Overall, our data indicate that population aging at the early stages narrows the gap between the wealthy and the poor but at the latter stages widens disparities in both wealth and income inequality because of a shift of the population toward older age groups with a much larger dispersion in income and wealth, which is not in contrast with the prediction of the life-cycle theory.

5 Conclusion and suggestions

The paper empirically investigates the consequence of population aging on wealth inequality, with special emphasis on potential nonlinearity. In a sample of developing and advanced countries, it finds that top wealth shares first decrease and then increase in the process of population aging. It also finds that as a population ages, the bottom 50% wealth share first increases and then decreases. The evidence holds even when accounting for regional and quantile effects. Our data thus suggest that

there exists a population aging threshold, above which population aging expands top wealth shares and depresses bottom wealth shares, widening wealth inequality, and below which population aging reduces top wealth shares and boosts bottom wealth shares, narrowing wealth inequality.

Likewise, population aging is found to exert a U effect on top income shares but an inverted-U effect on the bottom income share. Thus, population aging reduces income inequality at early stages of population aging but rises it at the latter stages. The evidence helps clarify the seemingly contradictory empirical results in the population aging-income inequality literature by stressing the importance of accounting for nonlinearity and even non-monotonicity in the process of population aging.

From a policy perspective, our evidence implies that there exists some optimal (threshold) level of population aging that minimizes wealth and income inequality. Either too high or too low level of population aging is detrimental to wealth and income distribution. In other words, some level of population aging might be needed to reduce inequality; however, too much population aging would be harmful. As population aging is going faster and deeper, and fertility holds key to slow down population aging, government policy toward supporting childbearing and parenthood is crucial for slowing down the speed of population aging and worsening inequality. These pronatalist policies include providing financial incentives such as family allowances and taxation benefits, and paid maternity and paternity leave policies may encourage childbearing and parenthood (Haan and Wrohlich 2011; Cohen et al. 2013). Since wealth can generate its income and accumulate through saving, and the rich and older people save at high rates than the poor and young people, apart from pronatalist policies, policies toward financial reforms that allow more people such as the poor and young to access and use financial services to save and invest may contain the adverse effect of population aging on wealth and income inequality.

To the best of our knowledge, this paper is the first to explore empirically the effect of population aging on wealth inequality and has established that population aging has a nonlinear and threshold effect on wealth inequality. The conclusions must be tempered, however, by some qualifications and reservations. The first is related to the endogeneity bias. So far there are no perfect econometric techniques that can fully control the endogeneity bias. Although GMM-type estimators directly confront the potential endogeneity bias induced by simultaneity, omitted variables, and unobserved country-specific effects, using internal instruments, the results do not settle the issue of causality. If variables are serial correlated, our estimates imply that population aging variables are a good predictor of wealth and income inequality, instead of causality. This calls for external instruments that satisfy the exclusive restriction. Moreover, in our empirical investigation, we have assumed there is a specific parametric form for the relationship between aging and inequality, which may lead to incorrect inference if the true relationship is not as specified. Thus, to provide more accurate policy suggestions, it is important for future research to consider a nonparametric regression approach in which the predictor does not take a predetermined form but is constructed according to information derived from the data.

Appendix

See Tables 7, 8, 9.

Table 7 A list of countries

Argentina	France	Mexico	Sweden
Australia	Germany	Morocco	Switzerland
Austria	Ghana	Namibia	Thailand
Bahrain	Greece	Netherlands	Tunisia
Bangladesh	Hong Kong	New Zealand	Turkey
Barbados	Hungary	Nigeria	Ukraine
Belarus	Iceland	Norway	United Arab Emirates
Belgium	India	Oman	United Kingdom
Botswana	Indonesia	Pakistan	United States
Brazil	Iran	Panama	Uruguay
Bulgaria	Ireland	Papua New Guinea	Venezuela, RB
Canada	Israel	Paraguay	Vietnam
Chile	Italy	Peru	West Bank and Gaza
China	Jamaica	Philippines	Zambia
Colombia	Japan	Poland	
Costa Rica	Jordan	Portugal	
Cote d'Ivoire	Kazakhstan	Qatar	
Croatia	Kenya	Romania	
Cyprus	Korea	Russian Federation	
Czech Republic	Kuwait	Saudi Arabia	
Denmark	Latvia	Singapore	
Ecuador	Lebanon	Slovak Republic	
Egypt	Luxembourg	Slovenia	
Estonia	Malaysia	South Africa	
Eswatini	Malta	Spain	
Finland	Mauritius	Sri Lanka	

Table 8 Descriptive Statistics

	topw1	topw10	botw50	top1	top10	bot50	oldrat	olddep	lifexp	gdpr	inf	findev	trade	polstab	ccorrupt	benefit
Panel A: Summary statistics																
Obs	613	620	620	712	712	712	736	736	736	721	699	582	719	644	644	332
Mean	29.838	62.219	4.306	15.344	43.421	16.01	2.035	2.473	4.283	3.178	1.432	3.92	4.313	0.163	0.41	2.592
Std. dev	8.959	8.83	3.057	5.356	10.144	5.147	0.731	0.703	0.117	3.122	1.369	0.819	0.57	0.924	1.027	2.908
Min	12.847	37.545	-4.907	4.438	22.483	5.048	-0.314	-0.161	3.765	-14.825	-2.897	-1.681	2.759	-2.702	-1.471	0.013
Max	55.87	89.265	17.375	34.712	71.55	29.752	3.324	3.842	4.441	17.328	7.952	5.505	6.039	1.688	2.434	14.861
Panel B: Correlation matrix																
topw1	1															
topw10	0.884*	1														
botw50	-0.634*	-0.835*	1													
Top1	0.775*	0.792*	-0.555*	1												
Top10	0.786*	0.821*	-0.550*	0.938*	1											
Bot50	-0.734*	-0.787*	0.505*	-0.878*	-0.957*	1										
oldrat	-0.545*	-0.537*	0.303*	-0.629*	-0.724*	0.713*	1									
olddep	-0.545*	-0.543*	0.309*	-0.640*	-0.738*	0.727*	0.993*	1								
Lifexp	-0.326*	-0.333*	0.191*	-0.354*	-0.454*	0.419*	0.521*	0.584*	1							
gdpr	0.089*	0.081*	0.021	0.229*	0.233*	-0.245*	-0.341*	-0.334*	-0.153*	1						
Inf	0.112*	0.093*	0.009	0.137*	0.149*	-0.128*	-0.196*	-0.225*	-0.457*	-0.027	1					
Findev	-0.187*	-0.147*	0.065	-0.261*	-0.285*	0.285*	0.412*	0.462*	0.609*	-0.200*	-0.517*	1				
Trade	-0.066	-0.098*	0.025	-0.123*	-0.128*	0.165*	0.045	0.082*	0.207*	0.082*	-0.267*	0.241*	1			
polstab	-0.298*	-0.288*	0.066	-0.459*	-0.476*	0.475*	0.430*	0.466*	0.433*	-0.088*	-0.357*	0.420*	0.402*	1		
ccorrupt	-0.310*	-0.259*	0.004	-0.424*	-0.469*	0.477*	0.474*	0.501*	-0.310*	-0.259*	0.004	-0.424*	-0.469*	0.477*	0.474*	
Benefit	-0.113	-0.106	-0.018	-0.151*	-0.232*	0.230*	0.318*	0.329*	0.350*	-0.125*	-0.188*	0.332*	-0.078	0.282*	0.392*	1

Note: All variables are in logs except for wealth shares (%), GDP growth (%), political stability, control of corruption, and benefit (%GDP). * p<0.1

Table 9 Panel VAR-Granger causality Wald tests in a bivariate system

Equation /Excluded	Chi-square (<i>p</i> value)	Accept or reject Ho
Panel A: Old-age dependence		
Old-age dependence/top 1% wealth shares	0.430 (0.512)	Accept Ho
Top 1% wealth shares/old-age dependence	4.119 (0.042)	Reject Ho
Old-age dependence/top 10% wealth shares	1.995 (0.158)	Accept Ho
Top 10% wealth shares/old-age dependence	3.581 (0.058)	Reject Ho
Old-age dependence/bottom 50% wealth shares	4.444 (0.035)	Reject Ho
Bottom 50% wealth shares/old-age dependence	0.311 (0.577)	Accept Ho
Old-age dependence/top 1% income shares	4.273 (0.039)	Reject Ho
Top 1% income shares/old-age dependence	5.702 (0.017)	Reject Ho
Old-age dependence/top 10% income shares	7.809 (0.005)	Reject Ho
Top 10% income shares/old-age dependence	4.377 (0.036)	Reject Ho
Old-age dependence/bottom 50% wealth shares	8.737 (0.003)	Reject Ho
Bottom 50% wealth shares/old-age dependence	6.833 (0.009)	Reject Ho
Panel B: Old-age population ratio		
Old-age dependence/top 1% wealth shares	0.490 (0.484)	Accept Ho
Top 1% wealth shares/old-age dependence	4.360 (0.037)	Reject Ho
Old-age dependence/top 10% wealth shares	2.509 (0.113)	Accept Ho
Top 10% wealth shares/old-age dependence	3.994 (0.046)	Reject Ho
Old-age dependence/bottom 50% wealth shares	4.194 (0.041)	Reject Ho
Bottom 50% wealth shares/old-age dependence	0.742 (0.389)	Accept Ho
Old-age dependence/top 1% income shares	4.868 (0.027)	Reject Ho
Top 1% income shares/old-age dependence	4.637 (0.031)	Reject Ho
Old-age dependence/top 10% income shares	11.888 (0.001)	Reject Ho
Top 10% income shares/old-age dependence	3.989 (0.046)	Reject Ho
Old-age dependence/bottom 50% wealth shares	7.341 (0.007)	Reject Ho
Bottom 50% wealth shares/old-age dependence	6.799 (0.009)	Reject Ho
Panel C: Life expectancy		
Life expectancy/top 1% wealth shares	0.448 (0.503)	Reject Ho
Top 1% wealth shares/life expectancy	4.162 (0.041)	Accept Ho
Life expectancy/top 10% wealth shares	3.162 (0.075)	Reject Ho
Top 10% wealth shares/life expectancy	4.416 (0.036)	Reject Ho
Life expectancy/bottom 50% wealth shares	4.274 (0.039)	Reject Ho
Bottom 50% wealth shares/life expectancy	1.973 (0.160)	Accept Ho
Life expectancy/top 1% income shares	6.072 (0.014)	Reject Ho
Top 1% income shares/life expectancy	3.805 (0.051)	Reject Ho
Life expectancy/top 10% income shares	15.598 (0.000)	Reject Ho
Top 10% income shares/life expectancy	5.229 (0.022)	Reject Ho
Life expectancy/bottom 50% wealth shares	11.788 (0.001)	Reject Ho
Bottom 50% wealth shares/life expectancy	3.501 (0.061)	Reject Ho

Ho: Excluded variable does not Granger-cause Equation variable

Ha: Excluded variable Granger-causes Equation variable

Funding No.

Data availability Data are available upon request.

Declarations

Conflicts of interest The author Joyce Hsieh declares that there's no relevant or material financial interests that relate to the research described in this paper.

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