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Wealth inequality in the long run: A Schumpeterian growth perspective*

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This paper extends Piketty's analysis of the wealth-income ratio used as a proxy for wealth inequality, to allow for innovation. Drawing on a Schumpeterian (R&D-based) growth model that incorporates both tangible and intangible capital and using historical data for 21 OECD countries, we find the wealth-income ratio to be significantly and positively related to R&D intensity and the fixed capital investment ratio, but negatively related to income growth. Accounting for the innovation-induced counteracting growth-effect on the wealth-income ratio, we show that the net effect of R&D on wealth inequality is positive.

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1 Introduction

The steady-state condition, $K/Y = s/(g + \delta)$, is pivotal in neoclassical growth models and many intertemporal models and states that the capital-income ratio, $K-Y$, is an increasing function of the gross saving rate, s , and a negative function of the economy’s growth rate, g , and fixed capital depreciation, δ . In *Capital in the Twenty-First Century*, Thomas Piketty calls this condition “the Second Fundamental Law of Capitalism” (Piketty, 2014, page 166) and argues that any deviation from this equation is just temporary as the economy will move towards its steady state.¹ Piketty and Zucman (2014) and Piketty (2015) use this condition to analyze the evolution of the wealth-income ratio, $W-Y$, as a proxy for wealth inequality and claim that, for advanced countries, the relatively low $W-Y$ ratio in the period 1920-1980 was deemed temporary because these economies were pulled off their steady states by shocks and because g was extraordinarily high.²

In this paper we extend the analysis of the $W-Y$ ratio to allow for innovation, noting that tangible capital is predominantly used in the analysis of the wealth-income ratio developed by Piketty and Zucman (2014), and subsequent works (Piketty, 2015, Madsen, 2017 and Madsen *et al.*, 2018b).³ This extension is increasingly relevant for the modern economies in which high earners are generally benefiting from intangible capital (e.g., R&D, copyrights, skills, brands, organizational know-how) rather than from the accumulation of physical capital (see, for a theoretical exposition, Peretto 2015, 2017). More explicitly, we provide a Schumpeterian interpretation of the evolution of the $W-Y$ ratio by deriving a steady-state condition for this ratio within an R&D-based growth framework. To this end, we use a variant of the canonical quality-ladder model developed by Grossman and Helpman (1991) which also allows for physical capital accumulation. In this set-up, technological progress resulting from costly and deliberative research aimed at the development of higher quality products is the major engine of growth. Aggregate wealth amounts to the sum of the market values of all the operating firms and the capital stock, whereas aggregate savings are equal to the sum of R&D and capital expenditure. The model predicts that the $W-Y$ ratio, β , is negatively related to the rate of economic growth, g , and positively related to R&D investment, $s_{R\&D}$, and fixed capital investment, s_K , both expressed as a percentage of GDP.

Drawing on this theoretical framework, our empirical analysis uses data for 21 OECD countries over the period 1860-2015 to identify the forces that drive the aggregate $W-Y$ ratio in the long run. More

¹In his book, Piketty uses the terms “capital” (K) and “wealth” (W) interchangeably, as if they were perfectly synonymous, and he defines capital as “the total market value of everything owned by the residents and government of a given country at a given point in time, provided that it can be traded on some market” (Piketty, 2014, page 48).

²There are several reasons why the $W-Y$ ratio is proxying inequality: since inequality in wealth holdings is higher than that of income, the overall income inequality will increase in response to an increase in the $W-Y$ ratio provided that the relative dispersions of W and Y are preserved (Krusell and Smith 2015). Furthermore, asset values directly affect earnings of high income employees through, e.g., bankers’ bonuses, CEO share options, owners of rental accommodation where the rent is linked to property values, and earnings of real estate employees that are linked to property values. Madsen (2017) gives several additional reasons why income and wealth inequality are increasing in the $W-Y$ ratio. Piketty (2015) suggests that the $W-Y$ ratio impacts directly on income inequality through the share of income going to capital using the first law of capitalism (Piketty, 2014, page 52).

³Piketty incorporates “immaterial capital” into his definition of capital (Piketty, 2014, page 49) treating the tangibles and the intangibles similarly.

specifically, we first test the prediction of the Schumpeterian model concerning the relationship between β and s_K , $s_{R\&D}$ and g using the Cross-Sectionally Augmented Distributed Lags (CS-DL) estimator of Chudik *et al.* (2016). This approach is based on a dynamic representation that yields estimates for the long-run parameters which are robust along a number of important dimensions but not to simultaneity feedbacks. For this reason, we assess the results with an array of alternative estimators, Auto-Regressive Distributed Lags (ARDL), IV-2SLS, regressions and Granger-causality analysis, to establish causality between β and s_K , $s_{R\&D}$ and g . Second, we take a more in-depth look at this relationship by investigating whether innovation contributes to reducing wealth inequality. This issue is fundamental because, in the conventional neoclassical growth framework adopted by Piketty and Zucman (2014) and Piketty (2015), an increase in the saving ratio is associated with a higher W - Y ratio in steady state. In the Schumpeterian model, which allows for saving/investment in R&D, innovation has two counterbalancing effects on the W - Y ratio. On the one hand, more investment in R&D raises the market value of innovative firms, which leads to an increase in the wealth-income ratio (wealth channel). On the other hand, a higher rate of innovation, induced by successful R&D activities, increases the economy's growth rate, and this ultimately reduces the W - Y ratio (growth channel). To track both mechanisms of transmission from innovation to the W - Y ratio, we estimate a simultaneous system of equations through the 3SLS estimator which explicitly accounts for both the wealth and growth effect. These estimates are then used to evaluate the overall (net) effect of R&D on the W - Y ratio.

As a preview of the results, we find that the wealth-income ratio, β , is significantly and positively related to both $s_{R\&D}$ and s_K , and significantly but negatively to g , over the entire period considered in this paper. These findings are robust to the inclusion of control variables, variations in the effect of the explanatory variables over different estimation periods and to the possibility that their impact changes across countries and time. Allowing for the innovation-induced counteracting growth-effect on the W - Y ratio, our estimates show that the net effect of R&D on wealth inequality is positive. The 800% increase in R&D intensity in the post-WWII period has contributed a 65% increase in the W - Y ratio, while it has contributed a 15% to the increase in the W - Y ratio since 1980. Conversely, we find that the decline in the net non-residential investment ratio since 1967 (1980) has resulted in a 15% (12%) decline in the W - Y ratio, suggesting that fixed capital has not been a source of the recent increase in wealth inequality over the past four decades.

The paper makes two principal contributions to the literature. First, we show that extending the analysis of the W - Y ratio to allow for innovation is not only important for the understanding of the forces driving the W - Y ratio but also gives a theoretical foundation for Piketty's Second Law for modern economies. This extension is crucial since innovation and intangible investment are the main drivers of growth in advanced economies, while fixed investment was the primary driver of growth in the 19th century or even before WWII (Galor and Moav, 2004).

Second, we construct a large macro dataset for 21 OECD countries spanning the period 1860-2015. This long dataset is exploited to trace the determinants of the W - Y ratio from the beginning of the Second Industrial Revolution with high wealth inequality, through industrialization with low inequality

and the transition into the post-industrial regime in which wealth inequality is gradually converging to the level that prevailed a century ago (Piketty and Zucman, 2014; Roine and Waldenström, 2015). The long panel data also give crucial econometric advantages: the panel estimator becomes more consistent as the sample grows, IV (instrument variable) estimates are substantially more consistent in large than small samples, and cross-country correlations of the disturbance terms can be allowed for (Bekker, 1994; Hahn and Hausman, 2005; Powell, 2017). The consistency gain is particularly large in IV regressions. As shown by Bekker (1994), even for reasonably good instruments, IV estimates are prone to be severely biased in small samples.⁴

Our paper contributes to the recent debate among academics on the robustness of Piketty’s theoretical apparatus and, more generally, to the discussion on the evolution of the W - Y ratio (see, e.g., Acemoglu and Robinson, 2015; Krusell and Smith, 2015; Blume and Durlauf, 2015; Mankiw, 2015; Weil, 2015). Of particular relevance to this paper is Krusell and Smith (2015), who argue that Piketty’s Second Law should be rewritten in gross terms; i.e., as $s/(g + \delta)$ instead of s^N/g , where s^N is the net saving rate. The net formulation implies savings behavior that is not empirically supported because Piketty assumes that the net saving rate is constant and positive. Thus, the gross saving rate tends to one as g approaches zero, which seems quite implausible. In the present paper, we adopt variables expressed in gross terms and constant prices, and also show that the results are not driven by housing, which is another criticism against Piketty’s work (Bonnet *et al.*, 2014). Another related paper to ours is Cozzi and Impullitti (2016) who develop a multi-country quality-ladder growth model with heterogeneous workers to explore the role of globalization for the W - Y ratio. Calibrating the model to the US economy, they show that the decline in the innovation technology gap between the US and the rest of the world has significantly increased the W - Y ratio in the US over the period 1980-2000.

Our paper is also related to a recent strand of the literature that uses a Schumpeterian growth approach to analyze the relationship between innovation and top income inequality. Jones and Kim (2014) show how a Pareto distribution for top income shares may result from a growth model in which entrepreneurs make efforts to increase their profits from their existing knowledge, while researchers seek new ideas to replace incumbents in the process of creative destruction. Finally, Aghion *et al.* (2018) develop a growth model with quality-improving innovations by incumbents and/or from potential entrants and show that facilitating innovation increases top income inequality as top incomes are earned by innovators.

⁴Consider the following first-stage and second-stage regressions:

$$\begin{aligned} x &= \delta + z\pi + v, & \text{First-stage} \\ y &= \gamma + \beta x + u, & \text{Second-stage} \end{aligned}$$

where z is a K -dimensional vector of instrumental variables that is independent of the error terms u and v . Bekker (1994) derives the probability limit:

$$\hat{\beta}_{2SLS} = \frac{\hat{Cov}(\hat{x}, y)}{\hat{Var}(\hat{x})} \rightarrow \beta + \frac{K/N \times Cov(u, v)}{Var(z\pi) + K/N \times Var(v)},$$

where N is the number of observations. This expression shows that the 2SLS estimator can yield severely biased parameter estimates in small samples. For N large, like the sample used here, the two-stage least squares estimator is an approximately consistent estimate of β , at least if K is small and if the instrument is valid.

The paper is structured as follows. Section 2 lays out the theoretical background and derives a Schumpeterian version of Piketty’s second law of capitalism. Section 3 describes the data and presents the econometric model and the estimation procedure used. Regression results and robustness checks are presented in Section 4. Section 5 investigates whether innovation contributes to the spread of wealth inequality and, finally, Section 6 concludes.

2 Theoretical setup

In this Section we extend the canonical quality-ladder growth model, developed by Grossman and Helpman (1991), to derive a Schumpeterian version of Piketty’s second law by allowing for physical capital accumulation.

2.1 Model assumptions and equilibrium conditions

There is a homogeneous final good, Υ , that is produced by fully competitive firms and that may be consumed or accumulated as physical capital. The economy has a fixed number of identical households that provide labor services in exchange for wages. Each individual member of a household lives forever and is endowed with one unit of labor, which is inelastically supplied. Households maximize

$$U \equiv \int_0^\infty e^{-\rho t} \log C(t) dt,$$

where ρ is the subjective discount rate, and $C(t)$ denotes their consumption of the homogeneous final good at time t . We take the final good as the numeraire and normalize its price, p_Υ , to 1 in every period. Production of the final output requires intermediate products, labor and capital goods and is produced according to the following constant-returns Cobb–Douglas production function

$$\Upsilon = A_\Upsilon L_\Upsilon^{1-\gamma-\nu} K^\gamma D^\nu \quad \text{with} \quad 0 < \gamma, \nu \quad \text{and} \quad \gamma + \nu < 1, \quad (1)$$

where A_Υ is a constant reflecting the choice of units, L_Υ is the amount of labor devoted to the production of final output, K denotes the aggregate capital stock, and D is an index of intermediate inputs, which is defined as

$$\log D(t) \equiv \int_0^1 \log \left[\sum_j q_j(\omega) d_{jt}(\omega) \right] d\omega,$$

where $d_{jt}(\omega)$ is the input quality j of intermediate good ω at time t , and $q_j(\omega)$ is its quality level.

Normalizing the quality of each input at time $t = 0$ to one, we denote quality j of product ω as $q_j(\omega) = \lambda^j$, where $\lambda > 1$ is the size of the quality improvement that an innovation brings.

Aggregate demand for labor, capital and intermediate inputs by producers of the final good can be written as

$$L_\Upsilon = (1 - \gamma - \nu) \frac{\Upsilon}{w_L}, \quad K = \gamma \frac{\Upsilon}{w_K}, \quad D = \nu \frac{\Upsilon}{p_D}. \quad (2)$$

where w_L is the wage rate of labor, w_K is the rental rate on capital, and p_D is the price index reflecting the prices of intermediate goods. Competition among suppliers of the final output leads to a price p_D equal to the minimum unit production cost, that is

$$p_D = \exp \left\{ \int_0^1 \log \left[\frac{\tilde{p}(\omega)}{\tilde{q}(\omega)} \right] d\omega \right\},$$

where $\tilde{p}(\omega)$ and $\tilde{q}(\omega)$ are the price and quality, respectively, of the brand of intermediate product ω that is sold at the lowest quality-adjusted price at time t . To produce D units of the final good, firms use $\tilde{d}(\omega) = Dp_D/\tilde{p}(\omega)$ units of this variety, and no units of any other brand of input ω . Using the fact that $D = \nu\Upsilon/p_D$ by Eq. (2), the aggregate demand for intermediate input ω can be expressed as $\tilde{d}(\omega) = \nu\Upsilon/\tilde{p}(\omega)$.

In the intermediate goods sector, labor is the only primary factor of production. Any intermediate good can be produced using one unit of labor, regardless of quality. Thus, the marginal cost of each intermediate input amounts to the wage rate, w_L . Producers of intermediate goods compete in prices. Since all innovations are carried out by followers, who find themselves exactly one step ahead of the former leaders, all intermediate inputs bear the same price, that is $\tilde{p}(\omega) = \tilde{p} = \lambda w_L$. Consequently, each quality leader earns a flow of profits given by

$$\pi = \left(\frac{\lambda - 1}{\lambda} \right) p_D D = \left(\frac{\lambda - 1}{\lambda} \right) \nu \Upsilon. \quad (3)$$

The R&D sector is characterized by a perfectly competitive environment, with free entry and constant return to scale technology. Any firm that invests resources in this activity at a rate \tilde{l} for a time interval of length dt will succeed with probability $\tilde{l}dt$. This requires an investment of $a_I \tilde{l}$ units of labor per unit of time. Let v denote the stock market value of an industry-leading firm. An entrepreneur can attain v with probability $\tilde{l}dt$ by investing resources $a_I \tilde{l}$ in R&D for an interval dt at the cost $w_L a_I \tilde{l}dt$. Therefore, in any industry ω allocating a positive and finite amount of labor to R&D, maximizing $v\tilde{l}dt - w_L a_I \tilde{l}dt$ leads to the following condition

$$v = w_L a_I. \quad (4)$$

We now turn to the stock-market valuation of profit-making enterprises. A no-arbitrage condition relates expected equity returns to the interest rate on a risk-free bond. Equity claims pay a dividend of πdt over a time interval of length dt , and appreciate by $\dot{v}dt$ if no entrepreneur innovates during this time period. However, if an innovation occurs during the interval dt , the shareholder suffers a capital loss of v . This event occurs with probability ιdt , where ι denotes the aggregate innovation rate. The expected rate of return to equity is $(\pi + \dot{v})/v - \iota$ per unit of time. Efficiency in the stock market requires that the expected rate of return from holding a share of an industry-leading firm is equal to the risk-free interest rate, r . Therefore, the no-arbitrage condition for the stock market becomes $\pi/v + \dot{v}/v = r + \iota$. Using

Eqs. (3) and (4), this condition can be expressed as

$$\left(\frac{\lambda-1}{\lambda}\right) \frac{\nu\Upsilon}{w_L a_I} + \frac{\dot{w}_L}{w_L} = r + \iota. \quad (5)$$

In the model a second no-arbitrage condition applies to the return to physical capital. Each capital good costs p_Υ to purchase and earns an instantaneous rental charge of w_K . Assuming that capital depreciates geometrically at the rate δ , the net profit from a purchase-and-rent strategy is $w_K - \delta p_\Upsilon + \dot{p}_\Upsilon$, which amounts to income from renting, w_K , minus loss of depreciation plus capital gain from the change in the price of capital. Taking account of our normalization ($p_\Upsilon \equiv 1$), the total yield on installed capital amounts to $w_K - \delta$. Equating this return to the interest rate, r , we get

$$w_K = r + \delta. \quad (6)$$

Let us now derive the market-clearing conditions that apply to the labor market and to the market for final output. Labor is used in R&D and in the production of intermediate and final goods. Total employment in the R&D sector equals $a_I \nu$. The quantity of labor used in intermediate production amounts to $\nu\Upsilon/(\lambda w_L)$. Demand for labor, L_Υ , in final good production equals $(1 - \gamma - \nu)\Upsilon/w_L$. The labor market equilibrium, in which the sum of labor demand equals labor supply, L , is given by

$$\left[1 - \gamma - \left(\frac{\lambda-1}{\lambda}\right) \nu\right] \frac{\Upsilon}{w_L} + a_I \nu = L. \quad (7)$$

Final output is either consumed or invested in capital equipment. Investment demand equals $\dot{K} + \delta K$, where \dot{K} represents the rate of increase in the capital stock. Households' consumption of the final good is equal to C . Market clearing therefore requires

$$\dot{K} + \delta K + C = \Upsilon. \quad (8)$$

2.2 Steady-state analysis

In what follows, we concentrate on the steady-state properties of the model. Eqs. (5) and (7) require that the long-run ratio between final output and the wage rate of labor, Υ/w_L , is constant, which implies that, in steady state, the wage rate grows at the same rate as final output. Then, Eq. (8) requires that the rate of investment, $(\dot{K} + \delta K)/Y$, and the consumption-to-output ratio, C/Υ , are both constant, which implies that capital, consumption and output must grow at the same rate in steady state, that is, $g_K = g_C = g_\Upsilon$. To compute this growth rate, we first need to derive the rate of change in the index of intermediate goods output, g_D . Since only state-of-the-art varieties are demanded in positive quantities, we substitute aggregate demand $\tilde{d}_t = \nu\Upsilon/(\lambda w_L)$ into $\log D(t)$ to obtain

$$\log D = \log \frac{\nu\Upsilon}{\lambda w_L} + \int_0^1 \log \tilde{q}_t(\omega) d\omega = \log \frac{\nu\Upsilon}{\lambda w_L} + \Phi_t \log \lambda, \quad (9)$$

where $\Phi_t \equiv \int_0^t \iota(\tau) d\tau$ is the expected number of R&D successes in the typical industry before time t . As the wage rate, w_L , grows over time at the same rate as does final output, Υ , and the innovation rate, ι , is constant along a balanced-growth path, differentiation of (9) yields

$$g_D = \iota \log \lambda.$$

Now, differentiating the production function of final output with respect to time we get $g_Y = \gamma g_K + \nu g_D$. Using the latter relationship, together with the fact that $g_K = g_Y$ and $g_D = \iota \log \lambda$, we can express the rate of growth of output in the steady state as

$$g_Y = \frac{\nu}{1-\gamma} g_D = \left(\frac{\nu \log \lambda}{1-\gamma} \right) \iota. \quad (10)$$

2.3 The distribution of income in the economy and the wealth-income ratio

The economy has two assets, namely claims on physical capital and equities in the intermediate good firms. As the economy has a continuum of industries of mass one and there is a single quality leader in each industry, the value of shares in the intermediate goods firms equals v . Thus, the aggregate stock of assets, W , can be written as $K + v$. Let us now specify the national budget constraint. Gross domestic product, Y , represents the total value added in the economy, which amounts to the sum of total output of the final good and the value created by the R&D sector, namely $\Upsilon + \nu \iota$.⁵ GDP can also be expressed as the sum of consumption and investment (savings) or, equivalently, as the sum of labor income, capital income and firm profits, namely

$$Y = \Upsilon + \nu \iota = \underbrace{C}_{\text{Consumption}} + \underbrace{w_L a_I \iota + \dot{K} + \delta K}_{\text{Savings}} = \underbrace{\left[1 - \gamma - \left(\frac{\lambda - 1}{\lambda} \right) \nu \right] \Upsilon + w_L a_I \iota}_{\text{Labor Income}} + \underbrace{w_K K}_{\text{Capital Income}} + \underbrace{\left(\frac{\lambda - 1}{\lambda} \right) \nu \Upsilon}_{\text{Firm Profits}}.$$

In this economy, national income is equal to total income net of capital depreciation, that is $Y - \delta K$. We denote $s_{R\&D} \equiv w_L a_I \iota / (Y - \delta K)$, which is the proportion of national income devoted to R&D investment, and $s_K = \dot{K} / (Y - \delta K)$, which is the proportion of national income devoted to investment in physical capital. The wealth-income ratio, β , is defined as the ratio between the aggregate stock of assets and national income, that is

$$\beta \equiv \frac{W}{Y - \delta K} = \frac{K + v}{Y - \delta K}.$$

The steady-state value of β can be determined by decomposing β as the sum of $K/(Y - \delta K)$ and $v/(Y - \delta K)$. As capital and final output grow at the same rate in the steady state, $K/(Y - \delta K)$ can be

⁵This follows from the definition of aggregate value added as the sum of value added in all sectors, namely $(\Upsilon - p_D D) + p_D D + \nu \iota$ where the expression in parenthesis is the value added in the final-good sector, whereas the second and the third term represent the value added in the intermediate-good sector and in the R&D sector, respectively.

written as

$$\frac{K}{Y - \delta K} = \frac{K}{\dot{K}} \times \frac{\dot{K}}{Y - \delta K} = \frac{s_K}{g_K} = \frac{s_K}{g_\Upsilon}.$$

Since $v = w_L a_I$ by Eq. (4) and $\iota = g_\Upsilon(1 - \gamma)/(\nu \log \lambda)$ by Eq. (10), $v/(Y - \delta K)$ can be written as

$$\frac{v}{Y - \delta K} = \frac{w_L a_I}{Y - \delta K} = \frac{1}{\iota} \cdot \frac{w_L a_I \iota}{Y - \delta K} = \frac{s_{R\&D}}{\iota} = \frac{s_{R\&D}}{g_\Upsilon} \times \frac{\nu \log \lambda}{1 - \gamma}.$$

Using these results, the wealth-income ratio, β , can be expressed as

$$\beta = \underbrace{\frac{s_K}{g_\Upsilon}}_{\text{Piketty}} + \underbrace{\frac{s_{R\&D}}{g_\Upsilon}}_{\text{Schumpeter}} \cdot \Gamma, \quad (11)$$

where $\Gamma \equiv \frac{\nu \log \lambda}{1 - \gamma}$. Eq. (11) extends Piketty's Second Law to allow for wealth accumulation driven by R&D. The model states that, in steady state, inequality is positively related to s_K and $s_{R\&D}$, and negatively related to the economic growth rate, g_Υ . While there is a one-to-one relationship between β and the s_K - g_Υ ratio, the influence of the $s_{R\&D}$ - g_Υ ratio on β is determined by Γ , where Γ positively depends on the innovation size, λ , which essentially measures the extent to which higher quality inputs improve upon lower quality inputs. Thus, an invention that has high commercial value because it markedly improves the quality of the product is capitalized at a high rate.

The W - Y ratio may temporarily deviate from its steady state due to factors such as war destruction of wealth, changing trade union power, and unexpected inflationary spells. Piketty and Zucman (2014), for example, argue that the reduced wealth and income inequality over the period 1920-1980 in the OECD countries was temporary because the W - Y ratio was pulled off its steady state and because the rate of economic growth was extraordinarily high.

3 Empirics: Model specification, data and causality

3.1 Model specification and estimation strategy

Our key equation, Eq. 11, predicts that the W - Y ratio, β , is positively related to the share of income spent on R&D and physical capital, $s_{R\&D}$ and s_K , and negatively related to the rate of economic growth, g . We test this prediction by estimating the following log-linear model for 21 OECD countries over the period 1860-2015. In the analysis we express the variables in gross terms, implying that income growth is defined as the growth rate of net domestic product plus the depreciation rate of total capital (tangible and intangible assets), namely $g' = g + \delta$:

$$\ln \beta_{it} = \eta_0 i + \eta_1 \ln s_{R\&D,it} + \eta_2 \ln s_{K,it} + \eta_3 \ln g'_{it} + \epsilon_{it}, \quad (12)$$

where i refers to country i , t to time period. The model predicts that $\eta_1 > 0$, $\eta_2 > 0$ and $\eta_3 < 0$.

Eq. (12) is estimated using the cross-sectionally augmented distributed lag (CS-DL) approach of

Chudik *et al.* (2016). This procedure allows us to identify the long-run impact of the regressors (η 's), by estimating Eq. (12) augmented with current and lagged values of first-differenced regressors.

To control for cross-sectional dependence induced by unobserved common shocks, we include time-varying cross-sectional averages of the dependent and explanatory variables as proxies for common correlated effects (CCE) as in Chudik and Pesaran (2015). While the use of conventional time dummies controls for the effects of global shocks that affect all countries equally, the CCE terms may account for spatial effects across a subset of countries, such as military conflicts between neighbouring countries, regional knowledge spillovers, etc. All these factors can induce cross-sectional error dependence and lead to inconsistent estimates if they are correlated with the explanatory variables.

The main advantage of the CS-DL estimator is that it yields consistent estimates of long-run parameters in a dynamic setting of analysis without being affected by the bias due to the presence of the lagged dependent variable (Nickell bias).⁶ However, given that the CS-DL estimator is not immune to simultaneity, we assess the robustness of the results by adopting an alternative long-run estimator (ARDL), which is valid even when the regressors are weakly exogenous, as well as by conducting IV regressions in which exogenous variation in the key regressors is predicted by variables external to the model. Furthermore, we relax the assumptions of the model and try to establish causality among variables through a Granger-causality analysis.

3.2 Data

The analysis is based on a dataset covering the period 1860-2015 for the following 21 OECD countries: Austria, Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, the Netherlands, Norway, New Zealand, Portugal, Spain, Sweden, Switzerland, the UK and the US. We measure β as the sum of the stock of R&D and fixed capital divided by GDP and, as an alternative, by the stock market capitalization over GDP in the robustness checks. The stock market capitalization is computed by multiplying the nominal capital stock and Tobin's q , as estimated in Madsen and Davis (2006). The fixed capital stock is derived from investment in residential housing, non-residential structures (buildings and structures) and equipment (machinery and equipment), using the perpetual inventory method and the depreciation rates of 3% for buildings and structures and 17% for machinery and equipment. The R&D stock, which is constructed as in Madsen and Ang (2016), is based on the perpetual inventory method using a 15% depreciation rate. Finally, $s_{R\&D}$ and s_K are measured in gross terms. As discussed above, income growth is expressed as the growth rate of net domestic product augmented with capital depreciation, $g'_{it} = g_{it} + \delta_{it}$. The depreciation rate is allowed to vary over time and across countries according to the weight that each type of asset has in capital stock (structures, machinery, equipment and R&D). It is important to allow for a time-varying depreciation rate since it has increased substantially over time along with the increasing share of machinery and equipment, and

⁶The CS-DL estimator has been shown to provide consistent estimates in a range of conditions, namely when variables are stationary or not, are serially correlated or in the presence of breaks in errors, dynamic mis-specification or strong cross-sectional dependence (Chudik *et al.*, 2016).

R&D, in total investment. Full details on data construction are given in the Web Appendix.

4 Regression results

We start our analysis in Section 4.1 by estimating Eq. (12) by means of a CS-DL specification assuming homogeneous effects of the variables across time and space. In Section 4.2 the model is subsequently extended with control variables that might affect the W - Y ratio and, at the same time, be correlated with the key explanatory variables. Section 4.3 accounts for cross-country and time-wise heterogeneity as well as for variations in estimation periods. Finally, simultaneity issues related to our long-run analysis are addressed in Section 4.4.

4.1 Baseline estimates

The baseline results of regressing Eq. (12) using the simple fixed-effects estimator are shown in Table 1, where income growth is always gross of depreciation except for the regression in column (3) which considers income growth net of capital depreciation, g . The coefficients of both $s_{R\&D}$ and s_K are significantly positive in the regression of column (1), in which residential investment is included in K and s_K . The coefficient of the physical investment rate is three times larger than that of R&D investment, mostly reflecting the size of fixed investment relative to that of R&D. In line with the prediction of our model, the coefficient of g' is negative. A one percent increase in $s_{R\&D}$ and s_K results in a 0.02-0.04 percent increase in the W - Y ratio. Conversely, a one percent increase in the rate of income growth results in a 0.02 percent reduction in the W - Y ratio.

Fixed capital stock and investment are based on non-residential investment in the regression, in columns (2)-(5); thus being more comparable to investment performed by the firms in knowledge-generating activities such as R&D. The coefficients are all highly significant and their absolute magnitudes are larger than the regression in column (1) in which capital also encompasses residential capital, suggesting that the capital-income ratio is particularly sensitive to private savings channeled to investment in productive capital (structures, machinery and equipment, etc.). Using g instead of $g + \delta$ (column 3) does not quantitatively change the results, suggesting that measuring income growth, net or gross of depreciation, is not that relevant for our long-run analysis.

In col. (4) the capital stock is based on a time-varying weighting scheme between different types of capital. Studies relying on historical data usually adopt measures of total capital based on the constant price value of the stock, rather than on the productive services of fixed capital. However, there could be distortions associated with the changing composition of aggregate capital over time and with the fact that productive services provided by each type of assets vary with the rate of technological obsolescence of the existing capital. For this reason we have built a measure of total capital that aggregates asset types using two-year chained weights (Tornqvist index). These weights reflect the share of each asset (structure, machinery, equipment and R&D) in total capital compensation based on their user cost, hence

Table 1: CS-DL estimates of W - Y ratio (1860-2015)

		1	2	3	4	5
R&D investment/GDP	$s_{R\&D}$	0.018*** (0.005)	0.029*** (0.010)	0.028*** (0.010)	0.025** (0.010)	0.025* (0.013)
Capital investment/GDP	s_K	0.043*** (0.004)	0.154*** (0.007)	0.153*** (0.007)	0.155*** (0.007)	0.174*** (0.010)
Income growth	g'	-0.020*** (0.002)	-0.050*** (0.005)	-0.048*** (0.004)	-0.051*** (0.005)	-0.034*** (0.006)
Fixed capital/investment	Total		Non-residential	Non-residential	Non-residential	Non-residential
Income growth	$g + \delta$		$g + \delta$	g	$g + \delta$	$g + \delta$
Index number	Fixed weights		Fixed weights	Fixed weights	Chained weights	Fixed weights
Wealth-income	Capital at replacement costs		Capital at replacement costs	Capital at replacement costs	Capital at replacement costs	Stock market capitalization
Obs.		3,276	3,276	3,276	3,276	3,276
R -squared		0.076	0.318	0.317	0.296	0.344

Notes: Cross-Sectionally Augmented Distributed Lags (CS-DL) estimates. Standard errors are in parentheses. Variables are measured in logs. The reported coefficients are long-run parameters. All regressions include country-specific fixed effects and common correlated effects, CCE (up to 5 year lags). Cols. 1-3 and 5 use variables expressed as number indexes based on fixed weights at a benchmark year (Laspeyres). Col. 4 uses variables expressed as number indexes based on two-year moving average weights (Tornqvist). W in Col. 5 is obtained by multiplying Tobin's q by the sum of fixed capital and R&D stock. ***, **, * significant at 1, 5 and 10%.

reflecting the flow of productive services provided by each type of capital (Jorgenson and Stiroh, 2000). The results using time-varying weights are quite similar to the benchmark results in col. (2), indicating that our findings are not sensitive to the mechanism of capital aggregation.

In the regression of the last column in Table 1, W - Y is measured as the ratio between non-residential capital stock as proxied by stock market capitalization and income, both expressed in nominal terms. Being based on market values as opposed to acquisition costs, this measure of wealth comes close to the estimates of Piketty and Zucman (2014), Piketty (2015), and Madsen (2017). While market capitalization better approximates wealth inequality than the value of capital stock based on acquisition costs, this measure is not perfectly consistent with our theoretical set-up and the models used by Piketty and Zucman (2014) and Piketty (2015), which are derived under the steady-state conditions that Tobin's q is equal to one, and hence that relative prices are constant. In col. 5 of Table 1, the coefficients of $s_{R\&D}$ and s_K are statistically highly significant and their magnitudes are similar to those of the other regressions, while the coefficient of g' is only slightly lower.

4.2 Including controls

Thus far we have included the variables that determine the W - Y ratio in the steady-state equilibrium. However, Piketty and Zucman (2014), Roine and Waldenström (2015) and Piketty (2015) suggest that the W - Y ratio was pulled off of its steady state during the approximate period 1920-1980 due to war destruction (which is accounted for in our estimates of fixed capital stock), inflation that eroded the real value of bonds, and shocks to expected post-tax returns to capital, such as tax hikes and credit constraints. If these variables were correlated to the focus regressors, and omitted from the regression, the parameters of investment rates and income growth might be biased. Estimation results with control variables are presented in Table 2, where, for comparative purposes, the regression in column (1) is a replica of our benchmark regression shown above (col. 2, Table 1).⁷

The regression in column (2) includes the share of private bank credit to the non-financial sector in GDP as a proxy for access to credit. Financial development is a vital control variable because it is a significant determinant of both income inequality and investment in R&D and fixed capital stock (Madsen and Ang, 2016, Madsen *et al.*, 2018a). In our setting, bank credit over GDP is significantly and positively related to the W - Y ratio, suggesting that financial development reduces the required returns to capital through more efficient intermediation and, consequently, leads to a higher capitalized value of capital income. This, however, does not change the effect of our key regressors.

The inflation rate is included in the regression in column (3). As stressed by Piketty (2015), inflation may erode the real value of wealth expressed in nominal terms and, at the same time, may reduce investment because it heightens the expected profitability of investment projects, therefore increasing

⁷Financial development is measured as the ratio of private bank credit/GDP, the inflation rate as the annual rate of change in the Consumer Price Index, whilst we use the direct tax rate as a proxy for fiscal burden (i.e., tax revenues over GDP at current prices). Trade openness is measured as the ratio of exports to total trade openness (imports plus exports). Note that using a measure of import intensity on total trade, or the ratio to GDP of exports or imports, does not significantly affect our inference.

Table 2: CS-DL estimates of the W - Y ratio (1860-2015): Control variables

		1	2	3	4	5	6
R&D investment/GDP	$s_{R\&D}$	0.029*** (0.010)	0.032*** (0.010)	0.029*** (0.010)	0.030*** (0.009)	0.031*** (0.010)	0.025*** (0.010)
Capital investment/GDP	s_K	0.154*** (0.007)	0.152*** (0.007)	0.155*** (0.007)	0.153*** (0.007)	0.140*** (0.007)	0.132*** (0.007)
Income growth	g'	-0.050*** (0.005)	-0.051*** (0.005)	-0.051*** (0.005)	-0.049*** (0.005)	-0.049*** (0.005)	
Financial development			0.077*** (0.007)				
Inflation rate				0.000 (0.007)			
Direct tax rate					-0.091*** (0.009)		
Trade openness						0.023 (0.027)	
Patenting rate							-0.145*** (0.026)
Obs.		3,276	3,276	3,276	3,276	3,068	3,269
R -squared		0.318	0.342	0.318	0.343	0.288	0.298

Notes: Cross-Sectionally Augmented Distributed Lags (CS-DL) estimates. Standard errors are in parentheses. Variables are measured in logs. The reported coefficients are long-run parameters. All regressions include country-specific fixed effects and common correlated effects, CCE (up to 5 year lags). Financial development is measured as the ratio of bank credit to GDP (col. 2); the inflation rate is measured as the rate of change in the Consumer Price Index (col. 3); direct tax rate is measured as the ratio of direct tax revenues to GDP (col. 4); Trade openness is measured as the ratio of exports to total merchandised products, i.e. imports plus exports (col. 5); the rate of patenting is measured as the ratio of patent applications to patent stock (col. 6). ***, **, * significant at 1, 5 and 10%.

the option value of postponing investment. Furthermore, inflation erodes the capitalized real value of depreciation of fixed capital for tax purposes. As column (3) shows, the coefficient of inflation is insignificant. This may reflect the fact that inflation equally affects the numerator and denominator of the W - Y ratio, or that it influences the W - Y ratio, through the explanatory variables that are included in our model.⁸

In column (4) we control for the tax burden. A large literature shows that taxation may affect macroeconomic performance in several respects, for instance, by lowering expected returns to investment and hence capital value, and reverberating on economic growth through the channels of productivity or factor accumulation (Gemmell *et al.*, 2011, 2014). Due to data availability, we are only able to control for direct taxation. The coefficient of this control is significantly negative, suggesting that direct taxes create a wedge between required returns and after-tax returns; thus initiating a capital de-cumulating process until after-tax returns are realigned to required returns.

Trade openness is included in the regression of column (5). The increasing inequality in the post-1980 period has often been attributed to increasing imports of goods produced by cheap unskilled labor that consequently reduced the demand for unskilled labor in the advanced countries. At the same time, trade openness may affect $s_{R\&D}$, as it expands the market for R&D-intensive products (see, among others, Dinopoulos and Segerstrom, 1999). However, the insignificance of trade openness indicates that this variable does not affect the W - Y ratio directly but at most through $s_{R\&D}$ (a finding that we show below in the IV estimates).

Overall, our key variables, $s_{R\&D}$, s_K , and g' , remain unaffected by the inclusion of the controls in all the regressions in columns (2)-(5), suggesting that the baseline estimates are not a result of the omission of some relevant factors that simultaneously influence the dependent and the independent variables.

Finally, in order to ascertain whether income growth pulls down the W - Y ratio as a reflection of successful innovations that stimulate economic growth (see Eq. 10), we include the rate of patenting in place of g' in the last column of Table 2.⁹ R&D investment (as a share of GDP), by contrast, enhances the W - Y ratio because it raises the stock market value of innovating firms. In Table 2, the coefficient of the patenting rate is negative and statistically significant, while the coefficient of $s_{R\&D}$ is comparable to that of the benchmark estimations (column 1). These results underscore the dual role of R&D and creative destruction for inequality, namely that an increase in R&D increases the W - Y ratio through accumulation of rents (and wealth), but it reduces the W - Y ratio through innovation-induced productivity advances. Thus, the higher is the R&D success rate (i.e., the rate of patenting), the lower is the effect of R&D on wealth inequality. This issue will be extensively discussed in Section 5.

⁸This result suggests that inflation can act as a potentially valid instrument for s_K .

⁹The innovation rate is approximated by the rate of patenting, defined as the ratio between new patent applications and the patent stock (Venturini, 2012).

4.3 Heterogeneous effects across countries and over time

In this section we allow the coefficients of the explanatory variables to vary across countries and over time. First consider the estimates in Table 3 in which we relax the assumption of parameter homogeneity. The regression in column (1) reports the baseline (CS-DL) estimates with homogeneous coefficients while accounting for cross-sectional dependence through the CCE terms. In column (2) we allow for cross-country coefficient heterogeneity by estimating the CS-DL specification for each individual country and subsequently compute the robust mean value of the parameters following the procedure devised by Bond *et al.* (2010). The coefficients of $s_{R\&D}$, s_K and g' remain statistically significant and have the expected signs. In comparison to the baseline estimates, the coefficient of g' is reduced, while the coefficient of $s_{R\&D}$ has increased. In the regressions of columns (3)-(5), we allow for parameter heterogeneity in the cross-sectional and the time dimensions using the Mean Observation OLS estimator, MO-OLS, developed by Neal (2016). This procedure assumes that the overall coefficient of a variable is the sum of unit-specific i , time-specific t and a common constant ($\theta_{it} = \theta + \theta_i + \theta_t$). Like the mean group estimator, θ_{it} is estimated for each individual country and averaged across countries. The MO-OLS estimator yields consistent estimates in moderate to large samples within both static and dynamic settings. However, its statistical properties are still unknown in settings with cross-sectional dependence. For this reason we report the MO-OLS estimates for our CS-DL specification i) without controlling for cross-sectional dependence (column 3), ii) controlling for weak cross sectional dependence with time dummies (column 4), and iii) allowing for strong cross-sectional dependence by means of CCE terms (column 5). The results are quite consistent across the MO-OLS regressions and the coefficients are statistically and economically highly significant. The magnitudes of the coefficients of $s_{R\&D}$ and s_K are larger than those of the homogeneous regression framework, suggesting that the assumption of parameter homogeneity biases the coefficients toward zero. Consequently, the baseline coefficients in column 1 are conservative and have to be regarded as lower-bound estimates.

Next, we check for stability of the coefficients $s_{R\&D}$, s_K and g' across time periods. We estimate the CS-DL specification with CCE terms and assume homogeneous coefficients as the relative short time span of the data may yield imprecise mean-group estimates compared to those obtained over the entire time period, 1860-2015. WWII is used as a breaking point because there was a significant positive structural shift of the growth regime at that time (Greasley *et al.*, 2013). We also include post-1970 regressions because was a period of emerging inequality and a transition to a regime of lower growth. The results are presented in Table 4. For the early estimation period, 1860-1945, the coefficients are comparable with the full-period estimates in Tables 1-3, except for the coefficient of s_K which now takes a lower value, suggesting that fixed capital accumulation was not a major driver of inequality during the period 1860-1945. Compared to the pre-1945 regressions, the coefficients of s_K and $s_{R\&D}$, are markedly higher in the post-WWII period, particularly after 1970. Similarly, the absolute value of the coefficient of g' increases after 1970 to a magnitude that is more consistent with neoclassical growth theory than in earlier periods. Overall, the post-1970 results are close to the predictions of Piketty's Second Law according to which the W - Y ratio should respond equiproportionally to changes in s_K and g' .

Table 3: CS-DL estimates of the W - Y ratio (1860-2015): Heterogeneity across countries and over time

		1	2	3	4	5
R&D investment/GDP	$s_{R\&D}$	0.029** (0.010)	0.056* (0.030)	0.065** (0.028)	0.143*** (0.036)	0.144*** (0.019)
Capital investment/GDP	s_K	0.154*** (0.007)	0.177*** (0.061)	0.331*** (0.030)	0.331*** (0.047)	0.277*** (0.015)
Income growth	g'	-0.050*** (0.005)	-0.025** (0.011)	-0.100** (0.042)	-0.053 (0.079)	-0.066*** (0.025)
Parameter		Homogeneous	Heterogeneous across countries	Heterogeneous across countries and over time	Heterogeneous across countries and over time	Heterogeneous across countries and over time
CSD control		CCE	CCE	NO TD/NO CCE	TD	CCE
Observations		3,486	3,066	3,276	3,276	3,276

Notes: Cross-Sectionally Augmented Distributed Lags (CS-DL) estimates. Standard errors are in parentheses. Variables are measured in logs. All regressions include country-specific fixed effects. The reported coefficients are long-run parameters. Control for cross-sectional dependence (CSD): CCE Common Correlated Effects (up to 5 year lags in cols. 1-2 and 3). TD time dummies. ***, **, * significant at 1, 5 and 10%.

Table 4: CS-DL estimates of the W - Y ratio (1860-2015): Variation in estimation periods

		1	2	3	4
		1860-2015	1860-1945	1945-2015	1970-2015
R&D investment/GDP	$s_{R\&D}$	0.029*** (0.010)	0.088*** (0.012)	0.055*** (0.011)	0.136*** (0.013)
Capital investment/GDP	s_K	0.154*** (0.007)	0.054*** (0.005)	0.670*** (0.017)	0.761*** (0.022)
Income growth	g'	-0.051*** (0.005)	-0.028*** (0.003)	-0.054*** (0.005)	-0.759*** (0.057)
Obs.		3,276	1,806	1,470	966
R -squared		0.318	0.291	0.644	0.750

Notes: Cross-Sectionally Augmented Distributed Lags (CS-DL) estimates. Standard errors are in parentheses. Variables are measured in logs. The reported coefficients are long-run parameters. All regressions include country-specific fixed effects and common correlated effects, CCE (up to 5 year lags). ***, **, * significant at 1, 5 and 10%.

4.4 Endogeneity and causality

Although the CS-DL estimator provides consistent estimates under most conditions, it does not allow for feedback from the dependent variable to the regressors, which may in turn lead to biased parameter estimates. In this section we perform three types of checks to assess whether our long-run estimates are biased by reverse causality. First, we estimate the empirical specification using the ARDL estimator, following Chudik *et al.* (2017). This estimator provides consistent parameter estimates in the presence of endogenous regressors when the lag structure of the variables is correctly specified, regardless of the order of integration of the variables (Pesaran and Shin, 1999). Second, we perform IV regressions by

means of two alternative sets of instruments (economic variables and natural disasters). Third, we relax the assumptions of the model and perform an unconditional panel vector auto-regression (VAR) analysis to establish Granger causality among variables.

Instrumental variables and identification strategy

The coefficients of s_K , $s_{R\&D}$ and g' might be endogenous because of feedback effects from the W - Y ratio to the regressors. An exogenous shock to the W - Y ratio might have an effect on the right-hand side variables until the economy transits towards its new steady-state equilibrium. To identify the impact of s_K , $s_{R\&D}$ and g' on the W - Y ratio, we first use a set of primary instruments, namely economic variables that have been found to be correlated with investment rates and income growth in earlier studies. For s_K , we use the agricultural share in GDP and the rate of consumer price inflation, both of which are likely to be associated with reduced fixed investment. A reduction in the agricultural share often connotes economic development in which a higher share of income goes to fixed investment. Higher inflation rates are usually associated with greater profit uncertainty of investment, consequently raising the option value of postponing investment projects. As instruments for $s_{R\&D}$, we use trade openness and secondary and tertiary educational attainments of the working age population. Trade openness, which is measured as the ratio of exports to total merchandised products (imports plus exports), increases the market size and, therefore, the expected returns to R&D investment. An educated workforce has been essential for formal and informal R&D throughout history (see, e.g., Meisenzahl and Mokyr, 2011; Madsen and Murin, 2017). For the post-1960 period, Wang (2010) and Becker (2013) find that tertiary education is a key determinant of R&D and that the typical inventor has a tertiary degree. Higher education links diverse areas of knowledge and enables problem solving that leads to knowledge breakthroughs. It expands knowledge in ways that may be of significant economic and technological importance. Neither trade openness nor education is likely to be affected by the W - Y ratio. Furthermore, education is predetermined as reflecting enrollment decisions taken in the past by workers entering and exiting the labor force. Finally, for g' , we use geographic proximity-weighted foreign rates of income growth.

Admittedly, our primary instruments are not perfect because they are all part of a complex economic system in which all variables are more or less endogenous. To cater for this weakness, we use a second set of instruments, exploiting variations in a catastrophic natural disasters. The economic literature on rare hazard events provides two main findings. First, in the aftermath of a catastrophic event, the level of economic activity is lower in the affected area; however, the disaster creates incentives to replace the destroyed capital stock and improve technologies, thus yielding positive productivity effects over the long-term horizon.¹⁰ Second, economic effects of natural disasters propagate spatially. For instance, financial resources are reallocated from affected areas to regions that are not directly involved in the event, thus stimulating investment activities in these areas (Hosono *et al.*, 2016). Due to the destruction and production interruptions, domestic demand re-orientates towards foreign goods, which explains why

¹⁰Natural disasters are found to be positively associated with human capital accumulation and total factor productivity growth (Skidmore and Toya, 2002), and stimulate innovations that reduce risks and damage of the catastrophic events (Miao and Popp, 2014).

the affected country’s imports increase after a major disaster, while exports fall (Gassebner *et al.*, 2010). Natural disasters therefore stimulate the adoption of foreign technologies (Cuaresma *et al.*, 2008). From the perspective of unaffected countries, foreign disasters raise internal demand and increase incentives of domestic firms to invest and innovate. On this basis, as instruments for investment rates, we use geographic distance-weighted measures of external disasters, i.e., catastrophic events affecting the other countries in our sample. Contrary to internal disasters, these events are exogenous to (and correlated with) domestic economic variables, and may better satisfy the exclusion restrictions (i.e., be unrelated to the ratio between domestic capital and income). To further mitigate reverse causality issues, we consider the cumulated frequency of external disasters over the previous five years (in place of damage or affected people), and weigh them with the inverse geographical distance. We prefer to use geographic distance as weights instead of trade flows since, as discussed above, these may respond to spatial propagations of the disaster’s effects. Specifically, we use the geographic distance-weighted number of external landslides and droughts as instruments for $s_{R\&D}$ and droughts and wildfires as instruments for s_K .¹¹ One limitation of the analysis is that, once we have accounted for the impact of external disasters channeled by these investments, we are not able to find any powerful instrument for g' . As a consequence, income growth is treated as weakly exogenous in this part of the analysis.

4.4.1 ARDL regressions

ARDL and CS-DL-IV estimates are presented in Table 5. Our benchmark estimates are again presented in column (1) for comparative purposes. In column (2) we report the long-run coefficients based on the ARDL specification augmented with CCE terms. Like the MO-OLS results, the absolute values of the coefficients are substantially higher than those of our benchmark regression shown in column (1), suggesting that the latter parameters may be biased toward zero.

4.4.2 IV regressions

The IV-regressions are presented in columns (3)-(5) of Table 5, where only one regressor is instrumented at a time to avoid the weak instrument problem. Following Bloom *et al.* (2013), the effect of each endogenous variable is estimated by means of a set of auxiliary (first-stage) regressions using the pairs of instruments illustrated above. These predicted values are then used as explanatory variables in the (second-stage) long-run CS-DL specifications.¹² The coefficients of the explanatory variables in the first-stage regressions in the lower panel of Table 5 are all significant at the 5-percent level and have the expected signs. The F -tests for excluded restrictions range between 11.3 and 78.3, suggesting that the

¹¹We use data on natural disasters from EM-DAT, the International Disaster Dataset, managed by the Centre for Research on the Epidemiology of Disasters (CRED), at the Université Catholique de Louvain (Belgium). This includes information on the number (occurrences) of mass hazard events, the estimated damage and the approximate number of people affected. CRED collects data from different sources and provides consistent series starting from 1900.

¹²First-stage regressions are estimated using static specifications including country fixed effects and common time dummies. Predicted variables enter the CS-DL regression in levels, first differences, or mean values. The second-stage regression uses standard errors bootstrapped with 200 replications.

Table 5: ARDL and IV estimates (1860-2015)

		1	2	3	4	5
		CSDL	ARDL	CSDL-IV	CSDL-IV	CSDL-IV
				2nd stage		
				Instrumented variables		
				$s_{R\&D}$	s_K	g'
R&D investment/GDP	$s_{R\&D}$	0.029*** (0.010)	0.283* [0.086]	0.058** (0.016)	0.053*** (0.014)	0.026* (0.015)
Capital investment/GDP	s_K	0.154*** (0.007)	0.667*** [0.000]	0.205* (0.117)	0.425*** (0.112)	0.132* (0.077)
Income growth	g'	-0.050*** (0.005)	-0.335*** [0.010]	-0.062*** (0.014)	-0.018*** (0.003)	-0.861*** (0.250)
	<u>Instruments</u>			1st stage		
	Educational attainments (2nd and 3rd)			0.034*** (0.006)		
	Trade openness			0.003*** (0.001)		
	Agriculture share of GDP				-0.055** (0.026)	
	Inflation				-0.151*** (0.036)	
	Foreign income growth					0.338*** (0.109)
	Foreign inflation					-2.528*** (0.204)
	F -test for excluded restrictions			22.49	11.33	78.29
	Obs.	3,276	2,436	2,436	2,436	2,436
	R -squared	0.318	0.993	0.382	0.215	0.293

Notes: Auto-Regressive Distributed Lags (ARDL) and Instrumental Variables (IV) regressions. Standard errors are in parentheses (bootstrapped in cols. 3-5). Variables are measured in logs. The reported coefficients are long-run parameters. All regressions include country-specific fixed effects. First-stage regressions include time dummies. Number of groups used in first stage: 21. Second-stage regressions include common correlated effects, CCE (up to 5 year lags). ***, **, * significant at 1, 5 and 10%.

Table 6: IV estimates based on external natural disasters (1900-2015)

		(1)	(2)	(3)	(4)	(5)
		CS-DL	CS-DL	ARDL	CSDL-IV	CSDL-IV
		1860-	1900-	1900-	1900-	1900-
		2015	2015	2015	2015	2015
		2nd stage				
		Instrumented variables				
					$s_{R\&D}$	s_K
R&D investment/GDP	$s_{R\&D}$	0.029*** (0.010)	0.030*** (0.011)	0.246* [0.054]	0.251** (0.098)	0.053*** (0.017)
Capital investment/GDP	s_K	0.155*** (0.007)	0.152*** (0.008)	0.335*** [0.002]	0.154 (0.104)	0.113* (0.073)
Income growth	g'	-0.051*** (0.005)	-0.051*** (0.005)	-0.162*** [0.005]	-0.052*** (0.010)	-0.014*** (0.004)
<u>Instruments</u>					1st stage	
Landslides					0.028*** (0.009)	
Droughts					0.023*** (0.005)	0.741*** (0.112)
Wildfire						0.637*** (0.109)
F -test for excluded restrictions					18.69 [0.000]	36.22 [0.000]
Obs.		3,276	2,436	3276	2436	2436
R -squared		0.318	0.303	0.9931	0.302	0.198

Notes: Auto-Regressive Distributed Lags (ARDL) and Instrumental Variables (IV) regressions. Standard errors are in parentheses (bootstrapped in cols. 3-5). Variables are measured in logs. The reported coefficients are long-run parameters. All regressions include country-specific fixed effects. First-stage regressions include time dummies. Number of groups used in first stage: 21. Second-stage regressions include common correlated effects, CCE (up to 5 year lags). ***, **, * significant at 1, 5 and 10%.

consistency loss in the second-stage regressions for potential violations of the exclusion restrictions are relatively low. In column (3) we instrument $s_{R\&D}$ and find, for this regressor, a coefficient of 0.06, which is between the estimates in the first two columns. In column (4) we predict the variation of s_K obtaining a coefficient of 0.43, which, again, is well above the baseline CS-DL estimates and much closer to the estimates yielded by the ARDL regression. Finally, in column (5) we treat g' as endogenous. We find that the coefficient of this variable is -0.86, and hence is close to the theory predictions.

Table 6 displays the regression results when natural disasters are used as instruments, recalling that the data on these events commence in 1900. For illustrative purposes, columns (1)-(3) report the results from our CS-DL regression over the periods 1860-2015 and 1900-2015, and the ARDL estimates over the period 1900-2015. The coefficients of natural disasters all have the expected positive sign in the first-stage regressions. The F -tests for excluded restrictions and the R -squared are quite high, indicating that, in the second-stage regression, the bias induced by any violation of the exclusion restrictions is likely to be low (lower panel columns 4 and 5). In the second stage, the coefficients of g' and $s_{R\&D}$ remain statistically significant, economically relevant and of the expected sign. The magnitude of the coefficient of $s_{R\&D}$ is particularly large when it is instrumented, again indicating that this coefficient may be downward biased in the baseline regressions and that instrumentation helps to expunge measurement errors and reduce attenuation bias. Finally, the coefficient of s_K is approximately of the same magnitude as that arising in the CS-DL regressions.

4.5 Granger-causality tests

To complete our study of causality, we perform a panel Vector Auto-Regression (VAR) analysis to assess the extent to which the dynamics of each variable is Granger-caused by the other covariates of the model. The econometric model used in this section is a fixed-effects panel VAR model, specified as

$$\mathbf{y}_{it} = \alpha_{i0} + \sum_{p=1}^P \Phi_p \mathbf{y}_{it-p} + \sum_{p=1}^P \Lambda_p F_{t-p} + \epsilon_{it} \quad (13)$$

where \mathbf{y}_{it} is the vector of variables, expressed in logs, $\mathbf{y}_{it}' = \{s_{R\&D,it}, s_{K,it}, g'_{it}, \beta_{it}\}$. Here, F_t captures unobserved common shocks that are a source of cross-sectional dependence among countries, modeled as CCE terms. We assume homogeneous parameters, Φ and Λ , and a homogeneous error structure. The equation system is estimated using the generalized method of moments (GMM), where the number of lags, p , is determined by the criteria developed by Andrews and Lu (2001).¹³

Table 7 reports χ^2 and p -values of the Granger-causality tests, and the total impact exerted by each regressor on the outcome variables. The panel VAR model is estimated over the entire period 1860-2015 as well as for the recent period, 1970-2015. The results for the overall time interval 1860-1915 in the left panel of Table 7 show that neither $s_{R\&D}$ nor g' are Granger-caused by the W - Y ratio at any conventional

¹³Panel-specific fixed effects are removed with the Helmert transformation. Standard errors are robust to heteroskedasticity and auto-correlation based on a Bartlett window.

Table 7: Panel Granger-causality tests

	1860-2015			1970-2015		
	χ^2	p -value	Impact	χ^2	p -value	Impact
Dep: $s_{R\&D}$						
s_K	14.3	[0.03]	0.001	2.95	[0.23]	0.057
g'	6.00	[0.42]	0.000	3.51	[0.17]	0.136
β	1.21	[0.98]	0.000	0.74	[0.69]	0.017
All	26.60	[0.09]		11.00	[0.09]	
Dep: s_K						
$s_{R\&D}$	15.2	[0.02]	0.205	2.72	[0.26]	-0.016
g'	9.7	[0.14]	-0.040	7.49	[0.02]	0.137
β	50.4	[0.00]	0.636	1.25	[0.54]	0.022
All	101.04	[0.00]		42.89	[0.00]	
Dep: g'						
$s_{R\&D}$	9.57	[0.14]	0.002	6.23	[0.04]	-0.042
s_K	9.97	[0.13]	0.315	0.82	[0.66]	-0.177
β	7.11	[0.31]	-0.276	0.33	[0.85]	0.024
All	32.27	[0.02]		9.35	[0.16]	
Dep: β						
$s_{R\&D}$	11.7	[0.07]	0.004	6.78	[0.03]	0.007
s_K	10.2	[0.12]	0.001	5.97	[0.05]	0.055
g'	25.3	[0.00]	0.004	3.87	[0.15]	0.034
All	50.7	[0.00]		18.40	[0.01]	

Notes: H0: the explanatory variables do not Granger-cause the dependent variable. The total impact is computed as the sum of the lagged coefficients of each regressor. The equation system is estimated with Generalized Method of Moments (GMM) using an optimal set (p) of lags selected with the criteria developed by Andrews and Lu (2001). Panel-specific fixed effects are removed with the Helmert transformation. Standard errors are robust to heteroskedasticity and auto-correlation based on a Bartlett window.

significance level. Conversely, s_K is Granger-caused by the W - Y ratio and R&D intensity, suggesting that s_K may not be exogenous. The results for the post-1970 period in the right panel of Table 7 indicate that the W - Y ratio is Granger-caused by $s_{R\&D}$, s_K and g' , and not the other way around. The coefficient of the W - Y ratio is always insignificant in the regressions in which $s_{R\&D}$, s_K and g' are treated as dependent variables, while both investment rates, $s_{R\&D}$ and s_K , are found to Granger-cause the W - Y ratio at the 5% level.

5 Does innovation lead to an increasing W - Y ratio?

In the conventional neoclassical growth framework, which is adopted by Piketty and Zucman (2014) and Piketty (2015), an increase in the saving/investment ratio is associated with a higher W - Y ratio in steady state. In our Schumpeterian economy, the link between innovative investment and wealth inequality is not clear-cut, as R&D has two counterbalancing effects on the W - Y ratio (see the discussion in Section 4.2). On the one hand, a larger proportion of GDP invested in R&D activities is associated to a higher ratio between corporate wealth and national income, as the incentive to innovate is driven by the market value of firms (*wealth channel*, WC). On the other hand, successful R&D activities raise the economy's rate of innovation and this, in turn, spurs the GDP growth rate. Through this mechanism, R&D ultimately reduces the ratio between the aggregate stock of assets and national income, W - Y (*growth channel*, GC). Other things being equal, a higher rate of innovation destroys the (temporary) rents associated with R&D, promoting a more uneven distribution of the resources in the economy. These two channels can be formalized as follows:

$$\begin{aligned} s_{R\&D} &\rightarrow \frac{s_{R\&D}\Gamma + \bar{s}_K}{g'} \rightarrow \frac{W}{Y} && \text{Wealth channel (WC)} \\ (s_{R\&D} \rightarrow \iota \rightarrow) \quad g' &\rightarrow \frac{\bar{s}_{R\&D}\Gamma + \bar{s}_K}{g'} \rightarrow \frac{W}{Y} && \text{Growth channel (GC)} \end{aligned}$$

where a bar over a variable means that the variable is kept constant, and ι is the rate of innovation (patenting).

By estimating the reduced-form equation for the W - Y ratio, the analysis developed thus far has focused on the wealth channel only. However, to identify both mechanisms at work and assess the net effect of R&D on the wealth-income ratio, we estimate the following system of equations:

$$\ln \iota_{it} = \xi_{0i} + \xi_1 \ln s_{R\&D,it} + \epsilon_{1,it}, \quad (14)$$

$$\ln g'_{it} = \zeta_{0i} + \zeta_1 \ln \iota_{it} + \epsilon_{2,it}, \quad (15)$$

$$\ln \beta_{it} = \pi_{0i} + \pi_1 \ln s_{R\&D,it} + \pi_2 \ln s_{K,it} + \pi_3 \ln g'_{it} + \epsilon_{3,it}, \quad (16)$$

where each equation is modeled as a CS-DL specification and hence system estimates denote long-run parameters. The system consists of a knowledge production function, the income (GDP) growth specification and the wealth-income equation. Following Crepon *et al.* (1998), we estimate the system by 3SLS

and derive the total (*net*) effect of $s_{R\&D}$ on the W - Y ratio:

$$\frac{\partial \ln \beta}{\partial \ln s_{R\&D}} = \frac{\partial \ln \beta}{\partial \ln s_{R\&D}} \Big|_{s_{R\&D}=\bar{s}_{R\&D}} + \frac{\partial \ln \beta}{\partial \ln s_{R\&D}} \Big|_{g'=\bar{g}'} = \frac{\partial \ln \beta}{\partial \ln g'} \cdot \frac{\partial \ln g'}{\partial \ln \iota} \cdot \frac{\partial \ln \iota}{\partial \ln s_{R\&D}} + \pi_1 = \underbrace{\xi_1 \zeta_1 \pi_3}_{GC} + \underbrace{\pi_1}_{WC} \quad (17)$$

where the first right-hand-side term is the growth effect and the second is wealth effect.

Table 8: **System estimates and total (*net*) effect of R&D intensity**

		1	2	3	4	5	6	7
		1860-2015		1860-2015			1945-2015	
		Benchmark		System			System	
		β	ι	g'	β	ι	g'	β
R&D investment/GDP	$s_{R\&D}$		0.015* (0.008)			0.040*** (0.012)		
Rate of innovation	ι			8.187*** (1.261)			3.869*** (0.846)	
R&D investment/GDP	$s_{R\&D}$	0.029*** (0.010)			0.037*** (0.011)			0.115*** (0.014)
Capital investment/GDP	s_K	0.155*** (0.007)			0.198*** (0.029)			0.278*** (0.040)
Income growth	g'	-0.051*** (0.005)			-0.130** (0.051)			-0.217*** (0.059)
Obs.		3,276	3,269	3,269	3,269	1,484	1,484	1,484
R-squared		0.319	0.510	-0.096	0.865	0.481	0.148	0.878
Wealth channel	WC				0.037			0.115
Growth channel	GC				-0.016			-0.034
Total (<i>net</i>) effect of R&D					0.021			0.081

Notes: 3SLS estimates of Eqs. (14)-(16). Each equation is modelled as a CS-DL specification. Standard errors are in parentheses. Variables are measured in logs. The reported coefficients are long-run parameters. All regressions include country-specific fixed effects and common correlated effects, CCE (up to 5 year lags). ***, **, * significant at 1, 5 and 10%.

The 3SLS regressions and the simulation results are presented in Table 8. Again, column (1) reports the results of our benchmark regression for the W - Y ratio. Cols. (2)-(4) show the results for the overall period 1860-2015 and cols. (5)-(7) present the post-WWII period. The parameter estimates of Eq. (16) in columns (4) and (7) are comparable to our benchmark results, suggesting that our results in Section 4 are robust to cross-equation residual correlation. The growth regressions in columns (3) and (6) indicate a highly significant relationship between the rate of economic growth, g' , and the rate of patenting, ι . This finding is consistent with the results of Madsen (2010) and Venturini (2012) in which productivity growth is regressed on patent intensity and other determinants and is in accordance with the Schumpeterian growth model in this paper (see Eq. 10 above).¹⁴ The results of regressing the innovation rate, ι , on R&D intensity, $s_{R\&D}$, are displayed in columns (2) and (5). The coefficient of R&D intensity is positive and highly significant, and increasing in magnitude over time, approximately doubling in the period between 1945 and 2015 compared to the entire time span, 1860-2015. The latter results are likely to reflect the

¹⁴This result gives strong support to Schumpeterian theories of economic growth which predict that research (patent) intensity is a driving force behind productivity growth (see, e.g., Aghion and Howitt 1998; Peretto 1998, 1999; Howitt 1999; Peretto and Smulders 2002).

larger errors in R&D measurement before than after WWII. Most innovations and inventions before around 1900 were outcomes of individual efforts and not necessarily related to systematic and directed research efforts by companies and universities (Mokyr, 2018). Since the early 1900s, innovative activity has become more systematically concentrated around universities and commercial research laboratories. This trend accelerated after WWII (Mokyr, 2018). Given the often unsystematic R&D undertakings before WWII and, particularly, before 1900, the quality of the R&D data deteriorate as we go back in time.

The net effects of R&D intensity on the W - Y ratio, based on Eq. (17), are shown in the lower panel of Table 8. Based on the estimates over the period 1860-2015 (cols. 4 and 7), a 100% increase in $s_{R\&D}$ is associated with a 2.1% increase in the W - Y ratio. While this overall effect may look small, it is noteworthy that $s_{R\&D}$ has increased by almost 800% since 1945 and has been approaching s_K , especially if we consider the increasing share of intangibles, along with R&D, in total firm investment (Corrado *et al.*, 2017). Based on the simulated effects from the post-WWII regressions, the 8-fold increase in $s_{R\&D}$ has resulted into a 65% increase in the W - Y ratio during the same period, suggesting that the increasing R&D share of total income has been highly influential for the increase in the W - Y ratio in the post-WWII period. Applying the elasticity of 0.081 to the percentage increase of $s_{R\&D}$ observed between 1980 and 2015 (185%), we also obtain that 15% of the increase in the W - Y ratio during this period has been determined by the rise in the R&D share of total income. This pattern of results is consistent with the analysis performed by Aghion *et al.* (2018), who find a positive and significant correlation between innovation and top income inequality in the US as successful R&D creates larger rents that are increasingly concentrated among individuals (and super-star inventors) at the top tail of the income distribution (see also Akcigit *et al.*, 2017).¹⁵

These results, however, should not lessen the importance of fixed capital investment for wealth inequality. The coefficient of s_K is significantly higher than that of $s_{R\&D}$ and, therefore, there is no counteracting growth-effect of tangible investment on the wealth-income ratio in steady state. Using the compromise estimate for the coefficient of s_K of 0.20 implies that the two-fold increase in s_K for the average country that we observe in our data from 1947 to 1967, increased the W - Y ratio by 20%. Conversely, the 75% (60%) decline in s_K resulting from our data over the period 1967-2015 (1980-2015), has resulted in a 15% (12%) decline in the W - Y ratio, suggesting that fixed capital has not been a source of the increasing wealth inequality that started in the early 1980s.

6 Conclusions

Since WWII the advanced countries have gradually transited from a growth regime dominated by fixed capital as the primary source of wealth to the post-industrial era in which knowledge accumulation is

¹⁵Following Piketty and Zucman (2014), an increasing W - Y ratio would expand the capital share on income, consequently leading to a shrink in the labor share. From this perspective, our results are consistent with the analysis performed by Koh *et al.* (2016), who document that the US labor share decline after WWII has been driven by the accumulation of intellectual property products capital.

gaining importance for inequality. Consistent with this observation, our paper extends Piketty's analysis of the W - Y ratio to allow for the influence of innovation and intangible capital. Using a variant of the quality-ladder model of Grossman and Helpman (1991), we show that the W - Y ratio and, hence, inequality in steady state is governed by research intensity, the fixed capital investment ratio and income growth. An implication of our Schumpeterian model is that R&D impacts inequality in two distinct ways: as the incentive to innovate is dictated by the market value of firms, a higher R&D intensity is associated with a greater corporate wealth-income ratio. Conversely, since economic growth in steady state is driven by innovation in R&D-based growth models, an increase in R&D intensity reduces inequality through promoting growth.

Based on data over the period 1860-2015 for 21 advanced countries, we perform a regression analysis yielding supporting evidence for the model by showing that the W - Y ratio is significantly and positively related to research intensity and the fixed capital investment ratio, but is negatively related to income growth. These results are robust to variations in estimation period, inclusion of controls, and allowance for parameter heterogeneity, reverse causality, and common correlated effects. Allowing for the innovation-induced counteracting growth-effect on the W - Y ratio, the simulations show that the net effect of R&D on inequality is positive. The 800% increase in R&D intensity in the post-WWII period has contributed a 65% increase in the W - Y ratio, while it has contributed 15% to the increase in the W - Y ratio since 1980. The simulations also show that the decline in the net non-residential investment ratio since 1967 (1980) has resulted in a 15% (12%) decline in the W - Y ratio, indicating that fixed capital has not been a source of the recent increase in wealth inequality over the past four decades.

Our paper also has some important implications for policy making. As the regressions show that the wealth-income ratio is more sensitive to the fixed investment ratio than to research intensity, our analysis suggests that policy makers should seek to promote and incentivize investment in knowledge-generating activities rather than investment in physical capital. Moreover, in order to strengthen the growth channel, R&D fiscal policies should be accompanied by supplementary measures aimed at raising research productivity, i.e., the rate of innovation from a given investment in R&D. These measures may include reforming the legal discipline of product and factor markets in order to increase the efficient allocation of research inputs, and implementing education policies aimed at expanding the scientific competencies of future inventors.

References

- Acemoglu, D. and Robinson, J. A. (2015). “The Rise and Decline of General Laws of Capitalism”. *Journal of Economic Perspectives*, **29**(1):3–28.
- Aghion, P., Akcigit, U., Bergeaud, A., Blundell, R., and Hémous, D. (2018). “Innovation and Top Income Inequality”. *Review of Economic Studies*, *forthcoming*.
- Aghion, P. and Howitt, P. (1998). *Endogenous Growth Theory*, volume 1 of *MIT Press Books*. The MIT Press.
- Akcigit, U., Grigsby, J., and Nicholas, T. (2017). “The Rise of American Ingenuity: Innovation and Inventors of the Golden Age”. Working Paper 23047, National Bureau of Economic Research.
- Andrews, D. W. and Lu, B. (2001). “Consistent Model and Moment Selection Procedures for GMM Estimation with Application to Dynamic Panel Data Models”. *Journal of Econometrics*, **101**(1):123–164.
- Becker, B. (2013). “The Determinants of R&D Investment: A Survey of the Empirical Research”. Discussion Paper Series 2013/09, Department of Economics, Loughborough University.
- Bekker, P. A. (1994). “Alternative Approximations to the Distributions of Instrumental Variable Estimators”. *Econometrica*, **62**(3):657–681.
- Bloom, N., Schankerman, M., and Van Reenen, J. (2013). “Identifying Technology Spillovers and Product Market Rivalry”. *Econometrica*, **81**(4):1347–1393.
- Blume, L. E. and Durlauf, S. N. (2015). “Capital in the Twenty-First Century: A Review Essay Review”. *Journal of Political Economy*, **123**(4):749–777.
- Bond, S., Leblebicioglu, A., and Schiantarelli, F. (2010). “Capital Accumulation and Growth: A New Look at the Empirical Evidence”. *Journal of Applied Econometrics*, **25**(7):1073–1099.
- Bonnet, O., Bono, P.-H., Chapelle, G., and Wasmer, E. (2014). “Does Housing Capital Contribute to Inequality? A Comment on Thomas Piketty’s Capital in the 21st Century”. Technical Report 2014-07, Sciences Po Department of Economics.
- Chudik, A., Mohaddes, K., Pesaran, M. H., and Raissi, M. (2016). “Long-Run Effects in Large Heterogeneous Panel Data Models with Cross-Sectionally Correlated Errors”. In “Advances in Econometrics”, volume 36. Essays in Honor of Aman Ullah, Emerald Publishing.
- Chudik, A., Mohaddes, K., Pesaran, M. H., and Raissi, M. (2017). “Is There a Debt-Threshold Effect on Output Growth?” *Review of Economics and Statistics*, **99**(1):135–150.

- Chudik, A. and Pesaran, M. H. (2015). “Common Correlated Effects Estimation of Heterogeneous Dynamic Panel Data Models with Weakly Exogenous Regressors”. *Journal of Econometrics*, **188**(2):393–420.
- Corrado, C., Haskel, J., and Jona-Lasinio, C. (2017). “Knowledge Spillovers, ICT and Productivity Growth”. *Oxford Bulletin of Economics and Statistics*, **79**(4):592–618.
- Cozzi, G. and Impullitti, G. (2016). “Globalization and Wage Polarization”. *The Review of Economics and Statistics*, **98**(5):984–1000.
- Crepon, B., Duguet, E., and Mairesse, J. (1998). “Research, Innovation and Productivity: An Econometric Analysis at the Firm Level”. *Economics of Innovation and New Technology*, **7**(2):115–158.
- Cuaresma, C. J., Hlouskova, J., and Oberstener, M. (2008). “Natural Disasters as Creative Destruction? Evidence from Developing Countries”. *Economic Inquiry*, **46**(2):214–226.
- Dinopoulos, E. and Segerstrom, P. (1999). “A Schumpeterian Model of Protection and Relative Wages”. *American Economic Review*, **89**(3):450–472.
- Galor, O. and Moav, O. (2004). “From Physical to Human Capital Accumulation: Inequality and the Process of Development”. *The Review of Economic Studies*, **71**(4):1001–1026.
- Gassebner, M., Keck, A., and Teh, R. (2010). “Shaken, Not Stirred: The Impact of Disasters on International Trade”. *Review of International Economics*, **18**(2):351–368.
- Gemmell, N., Kneller, R., and Sanz, I. (2011). “The Timing and Persistence of Fiscal Policy Impacts on Growth: Evidence from OECD Countries”. *Economic Journal*, **121**(550):33–58.
- Gemmell, N., Kneller, R., and Sanz, I. (2014). “The Growth Effects of Tax Rates in the OECD”. *Canadian Journal of Economics*, **47**(4):1217–1255.
- Greasley, D., Madsen, J. B., and Wohar, M. E. (2013). “Long-run Growth Empirics and New Challenges for Unified Theory”. *Applied Economics*, **45**(28):3973–3987.
- Grossman, G. M. and Helpman, E. (1991). “Quality Ladders in the Theory of Growth”. *Review of Economic Studies*, **58**(1):43–61.
- Hahn, J. and Hausman, J. (2005). “Estimation with Valid and Invalid Instruments”. *Annales d’Économie et de Statistique*, (79/80):25–57.
- Hosono, K., Miyakawa, D., Uchino, T., Hazama, M., Ono, A., Uchida, H., and Uesugi, I. (2016). “Natural Disasters, Damage to Banks, and Firm Investment”. *International Economic Review*, **57**(4):1335–1370.
- Howitt, P. (1999). “Steady endogenous growth with population and r & d inputs growing”. *Journal of Political Economy*, **107**(4):715–730.

- Jones, C. I. and Kim, J. (2014). “A Schumpeterian Model of Top Income Inequality”. NBER Working Paper No. 20637.
- Jorgenson, D. W. and Stiroh, K. J. (2000). “Raising the Speed Limit: US Economic Growth in the Information Age”. *Brookings Papers on Economic Activity*, **31**(1):125–236.
- Koh, D., Santaeuilàlia-Llopis, R., and Zheng, Y. (2016). “Labor Share Decline and Intellectual Property Products Capital”. Working Papers 927, Barcelona Graduate School of Economics.
- Krusell, P. and Smith, T. (2015). “Is Piketty’s Second Law of Capitalism Fundamental?” *Journal of Political Economy*, **123**(4):725–748.
- Madsen, J. B. (2010). “The Anatomy of Growth in the OECD since 1870”. *Journal of Monetary Economics*, **57**(6):753–767.
- Madsen, J. B. (2017). “Is Inequality Increasing in $r-g$? Piketty’s Principle of Capitalist Economics and the Dynamics of Inequality in Britain, 1210-2013”. CAMA Working Papers 2017-63, Centre for Applied Macroeconomic Analysis, Crawford School of Public Policy, The Australian National University.
- Madsen, J. B. and Ang, J. B. (2016). “Finance-Led Growth in the OECD since the Nineteenth Century: How Does Financial Development Transmit to Growth?” *The Review of Economics and Statistics*, **98**(3):552–572.
- Madsen, J. B. and Davis, E. P. (2006). “Equity Prices, Productivity Growth and ’The New Economy’”. *Economic Journal*, **116**(513):791–811.
- Madsen, J. B., Islam, M. R., and Doucouliagos, H. (2018a). “Inequality, Financial Development and Economic Growth in the OECD, 1870–2011”. *European Economic Review*, **101**:605–624.
- Madsen, J. B., Minniti, A., and Venturini, F. (2018b). “Assessing Piketty’s Second Law of Capitalism”. *Oxford Economic Papers*, **70**(1):1–21.
- Madsen, J. B. and Murin, F. (2017). “British Economic Growth since 1270: the Role of Education”. *Journal of Economic Growth*, **22**(3):229–272.
- Mankiw, G. (2015). “Yes, $r > g$. So What?” *American Economic Review, Papers and Proceedings*, **105**(5):43–47.
- Meisenzahl, R. R. and Mokyr, J. (2011). “The Rate and Direction of Invention in the British Industrial Revolution: Incentives and Institutions”. In “The Rate and Direction of Inventive Activity Revisited”, NBER Chapters, pages 443–479. National Bureau of Economic Research, Inc.
- Miao, Q. and Popp, D. (2014). “Necessity as the Mother of Invention: Innovative Responses to Natural Disasters”. *Journal of Environmental Economics and Management*, **68**(2):280–295.

- Mokyr, J. (2018). *The British Industrial Revolution: an Economic Perspective*. Routledge.
- Neal, T. (2016). “Multidimensional Parameter Heterogeneity in Panel Data Models”. University of New South Wales, mimeo.
- Peretto, P. (1998). “Technological Change and Population Growth”. *Journal of Economic Growth*, **3**(4):283–311.
- Peretto, P. (1999). “Cost Reduction, Entry, and the Interdependence of Market Structure and Economic Growth”. *Journal of Monetary Economics*, **43**(1):173–195.
- Peretto, P. (2015). “From Smith to Schumpeter: A Theory of Take-off and Convergence to Sustained Growth”. *European Economic Review*, **78**:1–26.
- Peretto, P. (2017). “Through Scarcity to Prosperity: A Theory of the Transition to Sustainable Growth”. Duke University, mimeo.
- Peretto, P. and Smulders, S. (2002). “Technological Distance, Growth and Scale Effects”. *The Economic Journal*, **112**(481):603–624.
- Pesaran, M. H. and Shin, Y. (1999). “An Autoregressive Distributed Lag Modelling Approach to Cointegration Analysis”. In S. Strøm, editor, “Econometrics and Economic Theory in the 20th Century: The Ragnar Frisch Centennial Symposium”, chapter 11, pages 371–413. Cambridge University Press, Cambridge.
- Piketty, T. (2014). *Capital in the Twenty-First Century*. Harvard University Press, London.
- Piketty, T. (2015). “Putting Distribution Back at the Center of Economics: Reflections on Capital in the Twenty-First Century”. *Journal of Economic Perspectives*, **29**(1):67–88.
- Piketty, T. and Zucman, G. (2014). “Capital is Back: Wealth-Income Ratios in Rich Countries, 1700–2010”. *Quarterly Journal of Economics*, **123**(3):1155–1210.
- Powell, J. L. (2017). “Identification and Asymptotic Approximations: Three Examples of Progress in Econometric Theory”. *Journal of Economic Perspectives*, **31**(2):107–124.
- Roine, J. and Waldenström, D. (2015). “Long-Run Trends in the Distribution of Income and Wealth”. In B. F. Atkinson, A.B., editor, “Handbook of Income Distribution”, volume 2A. Elsevier, Amsterdam.
- Skidmore, M. and Toya, H. (2002). “Do Natural Disasters Promote Long-run Growth?” *Economic Inquiry*, **40**(4):664–687.
- Venturini, F. (2012). “Looking into the Black Box of Schumpeterian Growth Theories: An Empirical Assessment of R&D Races”. *European Economic Review*, **56**(8):1530–1545.

Wang, E. C. (2010). “Determinants of R&D Investment: The Extreme-Bounds-Analysis Approach Applied to 26 OECD Countries”. *Research Policy*, **39**(1):103 – 116.

Weil, D. (2015). “Capital and Wealth in the 21st Century”. *American Economic Review, Papers and Proceedings*, **105**(5):34–37.