A Schumpeterian Exploration of Gini and Top/Bottom Income Shares - Supplementary Material

Tetsugen HARUYAMA

July 2023

Numbering of equations, figures and tables continues from the main text.

1 Calibration

1.1 Strategy

The main purpose of this calibration exercise is to quantify the contribution of the key underlying factors of the Xinequality relationship in the U.S. in recent decades. Our strategy has two steps, following Akcigit and Ates (2023).

In the first step, six parameters are set externally, and others are disciplined subject to data. In particular, we set the latter parameters on the basis of three types of data: (i) the entry rate of firms, (ii) the share of R&D workers in working population, and (iii) TFP growth. Given the series of $\hat{\xi}$ and $\hat{\zeta}$ in Panel (b) of Figure 6 (the main text), parameters are matched with (i) and (ii) for the 1981-2016 period, and (iii) for the average in the period. By so doing, we basically allow parameter values to change to be consistent with $\hat{\xi}$ and $\hat{\zeta}$. In the second step, we let all parameters change as in the first step, *except for* a single parameter which is held fixed at the 1981 level. Shutting down the effect of a parameter makes it possible to identify the extent to which it contributed to the X inequality relationship. We conduct this exercise for six parameters of interest to quantify the individual contribution of parameters to changes in inequality indices.

1.2 Calibrated Values and the Model Fit

Six parameters in Table 4 are externally set. The subjective rate of time preference ρ is set to 0.07 to roughly mimic the long-run annual rate of return from the stock market. γ is the parameter which

Externally Set Parameters				Internally Set Parameters	
ρ	0.07	τ	$0.30 \to 0.20$ (changes linearly)	J	1.249
γ	0.35	s_E	$0.05 \to 0.20$ (changes linearly)	δ_E, δ_I	Panels (c)-(f) of Figure 10
L	10.0	s_I	$0.05 \to 0.20$ (changes linearly)	$\overline{h}, \lambda$	

Table 4: Calibrated parameter values.

determines the degree of diminishing marginal product of R&D workers for entrant and incumbent firms. This parameter plays an important role in characterizing the nature of equilibrium. Kortum (1993) reports point estimates between 0.1 and 0.6. In a more recent attempt, Acemoglu, Akcigit, Hanley and Kerr (2016) runs a first-difference regression, reporting 0.286-0.455 with the the average of 0.35. They also conduct robustness checks, e.g. by restricting dataset, and obtain similar values. Acemoglu and Akcigit (2012) use those values for the analysis of IPR and innovation, and Acemoglu, Akcigit, Alp, Bloom and Kerr (2018) use 0.5. Given those studies, we set $\gamma = 0.35$, and the result does not dramatically change as long as $\gamma \leq 0.5$. We set the working population $L = 10.0$ for the following reason. In our model there are always a measure one of entrepreneurs earning positive monopoly profits, and those profits can be lower than wage. In this sense, entrepreneurs in our model are more like self-employed in data. The US Bureau of Labor Statistics compiles data of self-employed, incorporated and unincorporated both starting in 2000. Its ratio to the total employment is stable with the average of 10.7% in the 2000-2016 period, implying a roughly one in 10 are self-employed. $L = 10.0$ is used in line with this number.

Regarding a corporate profit tax rate and R&D subsidy rate, we borrow the values that Akcigit and Ates (2023) use. They provide a brief historical account for changes in those rates. Setting the corporate tax at 30% and the subsidy rate at 5% in 1981 in their calibration, the authors examine declining business dynamism in the US by changing those rates to 20% in 2010, respectively. Although they use a sophisticated approach of changing those rates over the period, we adopt a simpler approach of linearly changing them. Incumbent and entrant subsidy rates are equalized. The remaining parameters are internally set in the following way.

Panel (a) of Figure 10 shows the entry rate of establishments in the U.S, constructed using the Business Dynamic Statistics compiled by the Census Bureau. It is the ratio of new establishments to the total number of active establishments in a given year. Its long-run trend is negative, although it increased in early 1980 and before a steep dive due to the financial crisis in 2008. In Panel (b), the share of R&D workers is plotted, using the data from the OECD Main Science and Technology Indicators. It is defined as the ratio of the full-time equivalent number of researchers to the total employment. In contrast to the rate of firm entry, it steadily increases over the period. Finally, we also use the TFP growth rates, adjusted for capital utilization and labour efforts, which are reported in Fernald (2014).

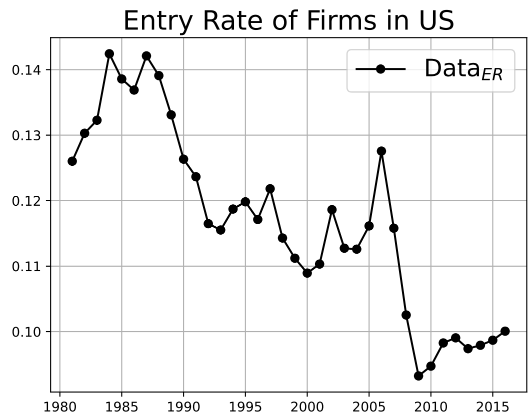
Using those values and given the $\left(\hat{\xi}, \hat{\zeta}\right)$ series in Panel (b) of Figure 6 (the main text), we set up the system of four equations to determine four parameters δ_I, δ_E, $\overline{h}$ and λ. The first equation is the rate of firm entry, which is given by

$$\mathrm{Data}_{ER} = \frac{g_E \hat{h}\left(\hat{\xi}\right)}{J} = \frac{\hat{\zeta}\hat{\xi}}{\left(\hat{\xi}+\hat{\zeta}\right)\left(\hat{\xi}+1\right)} \cdot \frac{\overline{h}}{J}. \tag{65}$$

where Data_{ER} is in Panel (a) of Figure 10. At each moment, g_E number of innovations occur across $i \in [0, 1]$, and each innovation creates $\hat{h}\left(\hat{\xi}\right)$ number of products. We take those products as establishments in data. $g_E \hat{h}\left(\hat{\xi}\right)$ is divided by J to make it consistent with the definition of the data on the LHS, which corresponds to a series in Panel (a) of Figure 10. Rewriting the first equality using (12), (22) and (25), we can use (65) to pin down the value of $\overline{h}$, given $\hat{\xi}$, $\hat{\zeta}$ and $\overline{h}$.

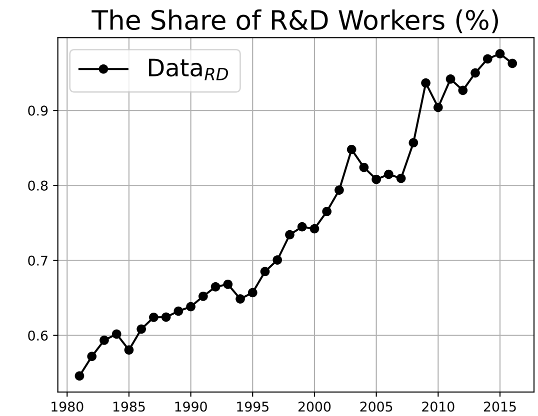
Let Data_{RD} denote a series in Panel (b) of Figure 10. Then, the share of R&D workers satisfies

Panel (a)



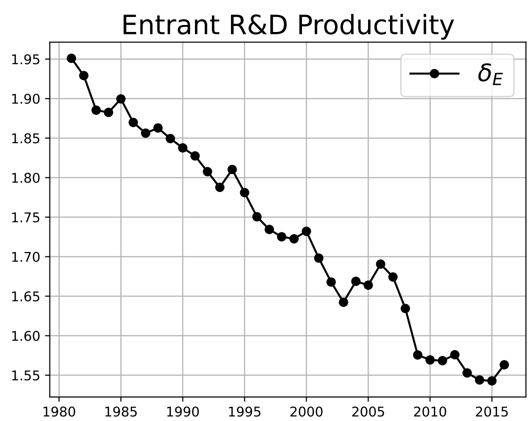
The entry rate is defined as the ratio of the number to the number of new establishments to the total number of establishments in a given year.
Data: the Business Dynamic Statistics, the Census Bureau.

Panel (b)

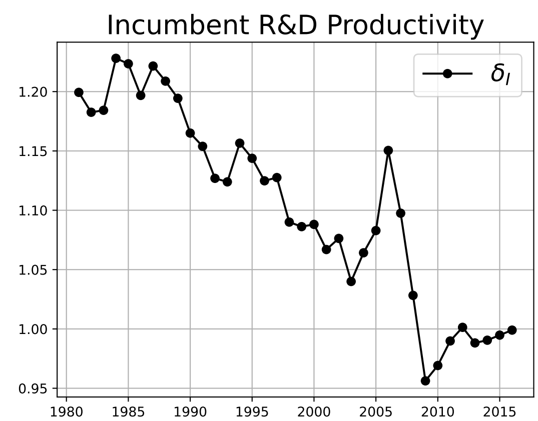


The ratio of the full-time equivalent number of researchers to the total employment.
Data: Main Science and Technology Indicators (2021)

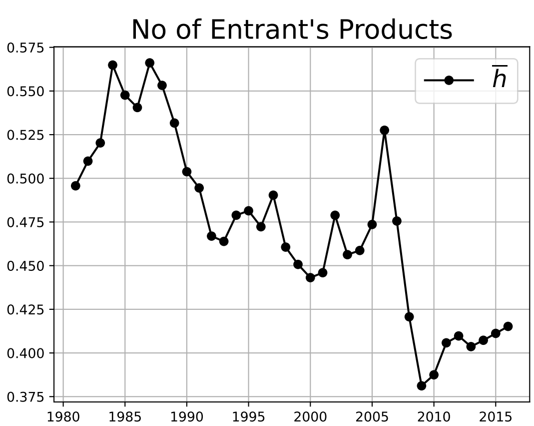
Panel (c)



Panel (d)



Panel (e)



Panel (f)

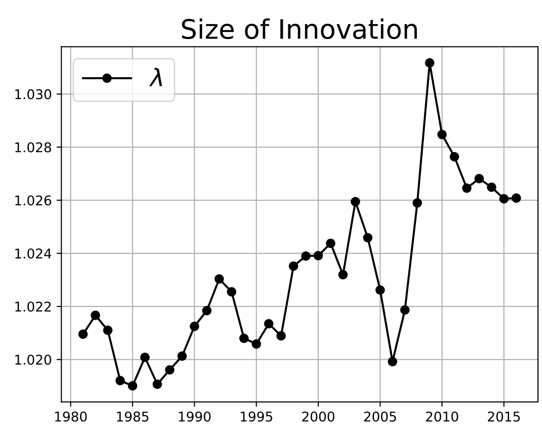


Figure 10: Panels (a) and (b) plot data, while calibrated values are shown in Panels (c)-(f).

		Model	Data	Source
(1)	TFP Growth	0.86%	0.86%	Fernald (2014)
(2)	Rate of Firm Entry	11.70%	11.70%	Business Dynamic Statistics, the US Census Bureau
(3)	Share of R&D Workers	0.75%	0.75%	OECD Main Science and Technology Indicators
(4)	Size of Innovation	1.023	1.075	Garcia-Macia, Hsieh and Klenow (2019)
(5)	Incumbent Contribution to TFP Growth	61.25%	75.17%	
(6)	Entrant Contribution to TFP Growth	38.75%	24.83%	

Table 5: The "Model" column shows the 1981-2016 averages. (1)-(3) in the "Data" columns are the average values in the 1981-2016 period, and those in (4)-(6) give the average of the three periods, 1983-1993, 1993-2003, 2003-2013.

the following condition

$$\text{Data}_{RD} = \frac{R_E\left(\hat{\xi}, \hat{\zeta}\right) + R_I\left(\hat{\xi}, \hat{\zeta}\right) N\left(\hat{\xi}, \hat{\zeta}\right)}{L}. \tag{66}$$

The remaining two conditions are the R&D incentive condition (47) and the ex ante firm value condition (48) which we use to make parameter values data-consistent. Making use of those, we simultaneously determine the values of δ_I, δ_E, $\overline{h}$ and λ over the 1981-2016 period for a given J. Finally, given these parameter values and using g_Q in (46), we set $J = 1.249$ to match the average annual TFP growth rate over the period, which is 0.859 from the data. This gives us recalculated values of δ_I, δ_E, $\overline{h}$ and λ.

The results are shown in Panels (c)-(f) of Figure 10. A noticeable feature is that R&D productivity levels, entrant and incumbent both, steadily fell. Importantly, the rate of reduction in δ_E is 19.9% which is greater than 16.7% for incumbents. This has the following implication for inequality. Those numbers mean that the RHS of (43) falls, tending to reduce the ratio of entrant to incumbent R&D employment. This translates into a reduction of the Right exponent ζ, making the right tail thicker. In fact, this result captures a falling trend of ζ in Panel (b) of Figure 6. A similar observation can be made for the Left distribution. Its Pareto exponent is given in (23), which is increasing in the figure.

$\overline{h}$ is the maximum initial number of products for entrants, and it fell by 16.2%, comparing the 1981 and 2016 values in Panels (e) of Figure 10. This follows the 20.6% reduction of the firm entry rate in data. An implication is that the income distribution becomes skew to the right. This tends to increase inequality, as will be discussed. The size of quality step λ in Panel (f) shows a slight increasing trend. $\overline{h}$ and λ give an impression that firms created less innovative products, but with larger quality steps.

Table 5 summarizes the model fit on the basis of the average values. Note that parameter values are chosen so that the model fits the data for (1)-(3), while (4)-(6) compare the model prediction with values reportetd in Garcia-Macia *et al.* (2019). The size of innovation λ is slightly lower than

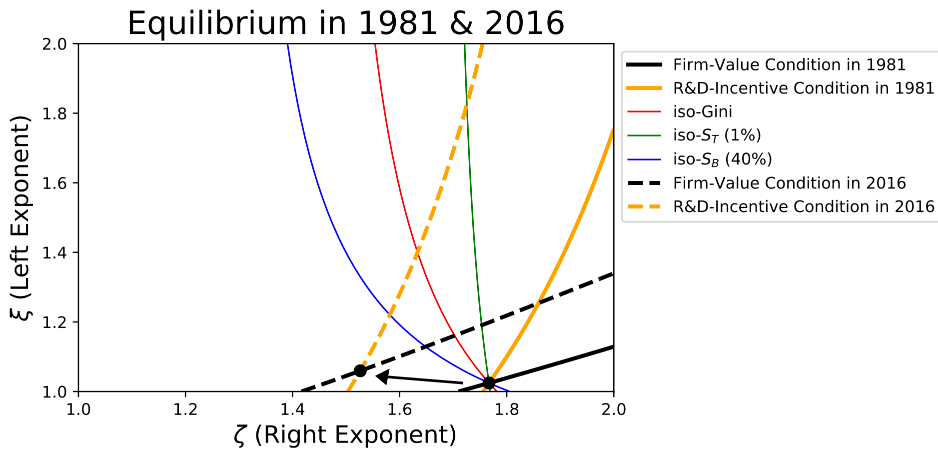


Figure 11: Based on calibrated values of the parameters, a movement of equilibrium from 1981 to 2016 is depicted with the R&D-incentive and firm-value conditions. Contours for a given Gini Coefficient, bottom 40% income shares and top 10% income shares for 1981 are also shown.

the value reported, but it falls in the range considered "plausible" by Stokey (1995).[1] λ is also the monopoly price markup over marginal cost. Its increasing trend is consistent with the fact that the markup increased in the US in recent decades, though the level of markup predicted by our model is relataively small.[2] (5) and (6) give the contribution of incumbent and entrant innovations to TFP growth. Though the model under- (or over-)predicts the incumbent (or entrant) contribution, those values are roughly in line with the data. In addition, Garcia-Macia *et al.* (2019) report that incumbent contribution increased while entrants' fell in the 1983-2013 period, and this trend is captured by our model.[3] Despite the parsimonious and stylized nature of the model, the fit of the model seems broadly reasonable. Figure 11 illustrates an equilibrium in 1981 based on calibrated parameter values. It shifts northeastward, generating the X inequality relationship, i.e. a higher Gini coefficient, a lower bottom income share and a higher top income share.

1.3 Quantifying Factors for the X Inequality Relationship

Calibrated parameter values used in Table 4 are data-consistent based on the Pareto exponents in Panel (b) of Figure 6. Put differently, our model can reproduce those series of $\hat{\xi}$ and $\hat{\zeta}$. More importantly, we can also reproduce Double-Pareto Prediction series of the Gini coefficient and top/bottom income shares in Panels (a)-(e) of Figure 7, using the R&D-incentive and firm-value conditions with those calibrated parameter values. Viewed from the model's perspective, therefore, changes in ξ, ζ and the inequality indices are the results of changing all parameters *at the same time*.

Given this observation, we quantify the contribution of each parameter to the X relationship, using a method similar to the one employed in Akcigit and Ates (2023). We conduct counter-

[1] Stokey (1995) considers $[1.02, 1.6]$ as a plausible range. Acemoglu and Cao (2015) use 1.1 and 1.2 for simulation, which are also in the range.

[2] Evidence cited in Akcigit and Ates (2021) shows that the markup increases from 20% to 50% between 1980 and 2010.

[3] According to Garcia-Macia *et al.* (2019), entrant contribution is 32.3% in 1983-1993 and fell to 19.8% in 2003-2013. In our model, the corresponding percents is 41.6% and 36.3%.

Table 6:

Measure: Ω_1	D: Double-Pareto Approximated Series								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	δ_E	δ_I	$\overline{h}$	λ	τ	$s_I = s_E$	δ_E and $\overline{h}$	τ and $s_I = s_E$	(7)/(8)
Gini Coefficient	1.66	−3.00	0.67	0.69	0.43	0.55	1.79	0.92	1.94
Top 1% Share	1.64	−3.43	0.68	0.43	0.28	0.35	1.83	0.57	3.24
Bottom 40% Share	1.43	−3.58	0.69	1.32	0.81	1.04	1.28	1.78	0.72

Table 7:

Measure: Ω_2	D: Double-Pareto Approximated Series								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	δ_E	δ_I	$\overline{h}$	λ	τ	$s_I = s_E$	δ_E and $\overline{h}$	τ and $s_I = s_E$	(7)/(8)
Gini Coefficient	0.91	−1.75	0.20	0.27	0.22	0.27	0.93	0.92	1.01
Top 1% Share	0.88	−2.07	0.20	0.16	0.13	0.16	0.93	0.57	1.64
Bottom 40% Share	0.80	−2.08	0.21	0.54	0.43	0.52	0.73	1.78	0.41

factual experiments by holding one parameter at the 1981 level at a time, while other parameters change as documented in Table 4. Inevitably, the inequality indices deviate from the original series, and such deviation allows us to measure the contribution of a parameter held fixed. We repeat this process for δ_E, δ_I, $\overline{h}$, λ, τ and $s_I = s_E$. To quantify deviation, we use the following measures:

$$\Omega_1 = \frac{D_{2016} - D^k_{2016}}{D_{2016} - D_{1981}}, \qquad \Omega_2 = \frac{\frac{1}{d}\sum_{y=1981}^{y_{\text{end}}} \left(D_y - D^k_y\right)}{D_{y_{\text{end}}} - D_{1981}} \tag{67}$$

D refers to the Gini coefficient, the top 10% income share or the bottom 40% income share, and k is a variable fixed at the 1981 level.[4] For example, D_{2016} is the Gini coefficient in 2016 and D^k_{2016} is the Gini coefficient in 2016 with a variable k is fixed at the 1981 level. d is the number of years used in the numerator in Ω_2. Note that Ω_1 measures deviation in 2016, while Ω_2 uses the average of deviation as a measure of the contribution of a variable k.[5] Also note that the larger the value of Ω_1 and Ω_2, the greater the contribution made by a variable k. If Ω_1 or Ω_2 is negative, it means a negative contribution being made by a variable k.

Consider entrant R&D productivity δ_E. It is best explained using Panel (a) of Figure 12. The Gini coefficient, the bottom 40% income share and the top 1% income share are shown, and series labelled "Double-Pareto Prediction" and "Data" are equivalent to those in Panels (a), (b) and (e)

[4] A similar index is used in Akcigit and Ates (2023).

[5] In (67), y_{end} is the end year which may differ for the reason mentioned in Footnote 6.

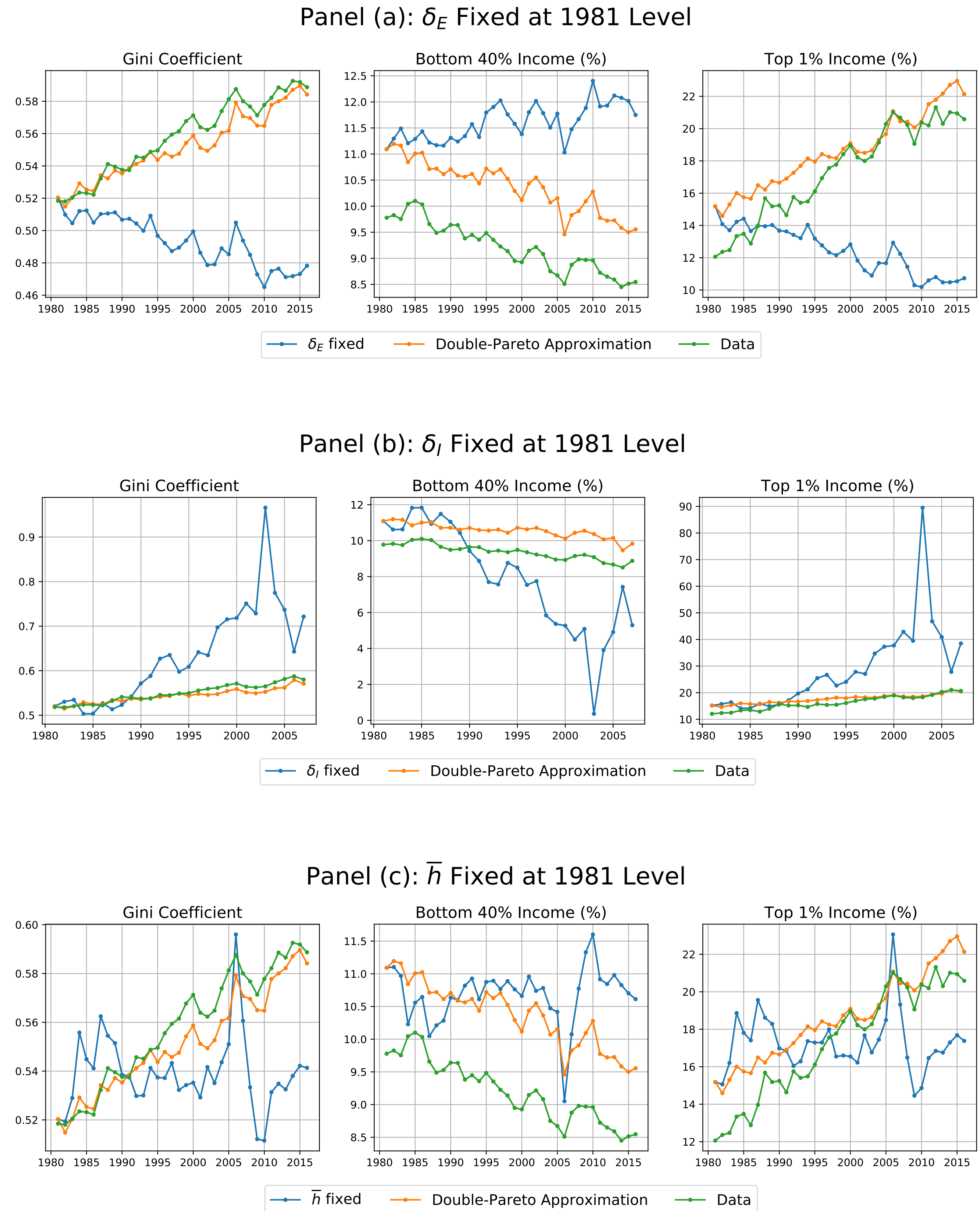

Panel (a): δ_E Fixed at 1981 Level
Gini Coefficient
Bottom 40% Income (%)
Top 1% Income (%)
δ_E fixed
Double-Pareto Approximation
Data
Panel (b): δ_I Fixed at 1981 Level
Gini Coefficient
Bottom 40% Income (%)
Top 1% Income (%)
δ_I fixed
Double-Pareto Approximation
Data
Panel (c): $\overline{h}$ Fixed at 1981 Level
Gini Coefficient
Bottom 40% Income (%)
Top 1% Income (%)
$\overline{h}$ fixed
Double-Pareto Approximation
Data

Figure 12:

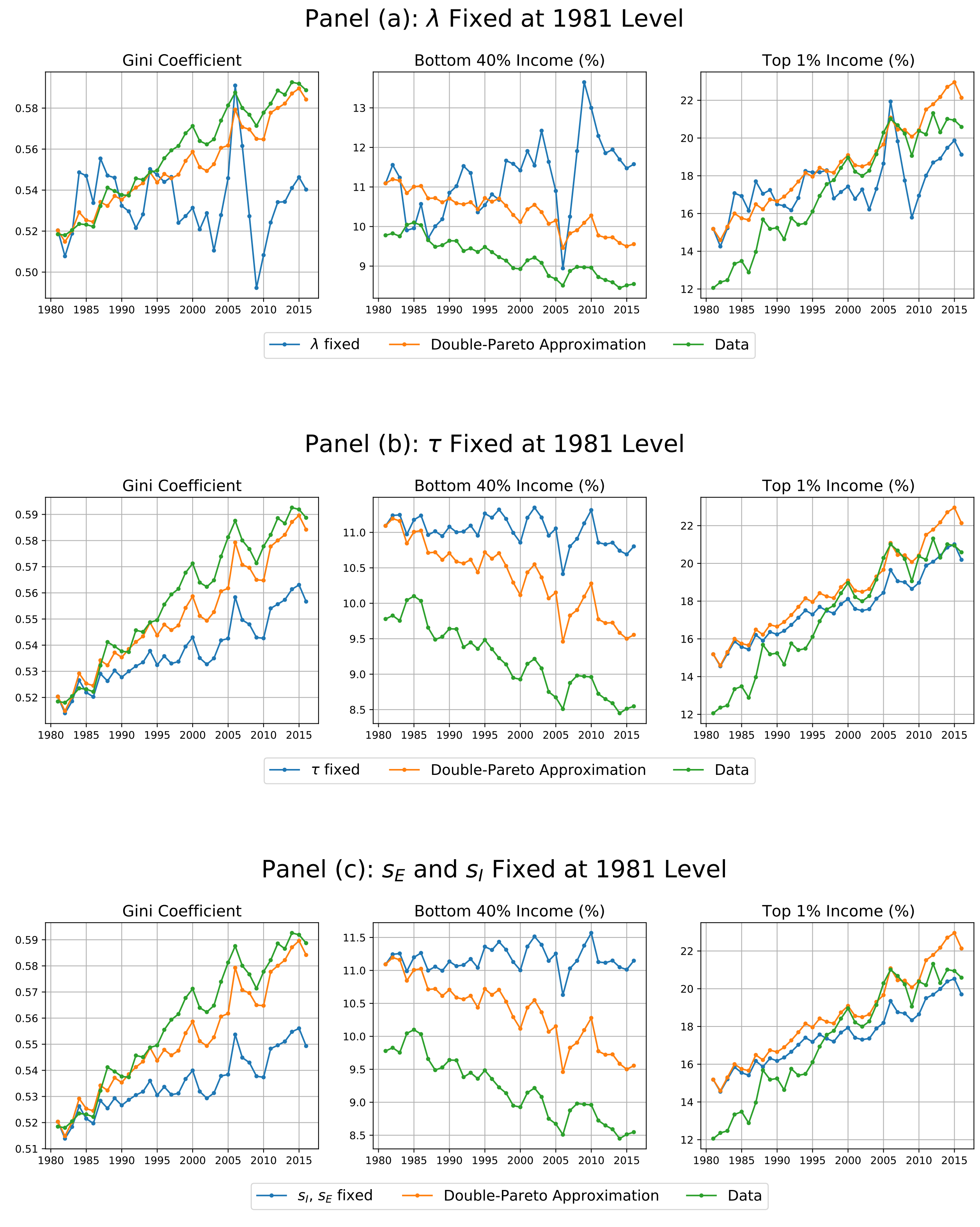

Panel (a): λ Fixed at 1981 Level
Gini Coefficient
Bottom 40% Income (%)
Top 1% Income (%)
λ fixed
Double-Pareto Approximation
Data
Panel (b): τ Fixed at 1981 Level
Gini Coefficient
Bottom 40% Income (%)
Top 1% Income (%)
τ fixed
Double-Pareto Approximation
Data
Panel (c): s_E and s_I Fixed at 1981 Level
Gini Coefficient
Bottom 40% Income (%)
Top 1% Income (%)
s_I, s_E fixed
Double-Pareto Approximation
Data

Figure 13:

of Figure 7. Series labelled "δ_E fixed" show what would happen if the parameter was held constant at the 1981 level. Consider the left graph. For a constant δ_E, the Gini coefficient falls rather than rises. It means that the effect of a reduction of δ_E is so strong that if it is removed, then the Gini coefficient follows a clear negative trend. In this sense, a falling δ_E made a significant contribution to an increase in the Gini coefficient. A similar pattern arises in the right graph of the top 1% income share. It would have fallen below 10% in 2010 if entrant R&D productivity had been left unchanged in 1981. The middle graph shows the bottom 40% income share. A δ_E-fixed series is trend-less or has a slightly positive trend, while the Data and Double-Pareto Prediction series fall. It confirms that a fall in δ_E had large impacts on different aspects of inequality.

Turning to Panel (b), it shows the case of fixing incumbent R&D productivity δ_I. In sharp contrast to δ_E, the trends of the δ_I-fixed series are all reversed.[6] For example, consider the Gini coefficient. If δ_I was fixed at the 1981 level, it would have increased as shown in the left graph. It means that a decreasing incumbent R&D productivity mitigated inequality measured by the Gini coefficient. The top 1% share in right graph is similarly interpreted. In the case of the bottom 40% income share in the middle graph, it would have been as low as 4% (ignoring an observation with less than 1% in 2003) with a δ_I fixed at the 1981 level. These imply that the worsening of inequality is mitigated due to a declining incumbent productivity.

An intuition for these results of entrant and incumbent R&D productivity levels is straightforward. Consider the case of δ_E being fixed first. If δ_E is kept at the 1981 level, changes in g_E become minimal, while a falling δ_I tends to reduce g_I. As a result, the left and right Pareto exponents $\xi = (1 - g_E)/g_I$ and $\zeta = g_E/g_I$ both tend to increase. In Figure 5, this means that an economy moves northeastward from $A0$ for a constant δ_E. Fixing δ_I is the opposite case where equilibrium moves southwestward.

To quantify the contrasting results of fixing δ_E and δ_I, let us turn to Columns (1) and (2) of Table 6. It uses the end-year deviation Ω_1 as a measure of contribution with the Double-Pareto approximated series used for D in (67). The numbers in Column (1) are all positive, while negative in Column (2). The same pattern remains in Table 7 with the average cumulative measure Ω_2. These results concerning the relative roles of incumbent/entrant firms are in line with Garcia-Macia *et al.* (2019) which find a dwindling role of entrant innovation in TFP growth in the 1983-2013 period.

The same quantifying approach is applied to $\overline{h}$, λ, τ and $s_E = s_I$. Panel (c) of Figure 12 shows that the $\overline{h}$-fixed series are trend-less, though they are more volatile compared with the δ_E-fixed series. It means that a falling $\overline{h}$ increases the inequality indices, though its effect is less than δ_E, as confirmed in Column (3) of Tables 6 and 7. Panel (a) of Figure 13 shows the case of the quality step λ. It exhibits a volatile pattern similar to $\overline{h}$, and its impacts are also comparable to $\overline{h}$, as Column (4) of the tables confirm. In Panels (b) and (c) of the figure, the τ-fixed and $s_E = s_I$ fixed series follow more steady patterns. Visual inspection of the graphs indicates their significant impacts, which are confirmed in Columns (5) and (6) of Tables 6 and 7.

1.4 Declining Business Dynamism and Fiscal Policy Changes

Having considered the impacts of each parameter separately, there are two issues that we consider next. First, how are those parameter changes interact in generating the X inequality relationship? Do they reinforce or impede each other? Second, the following patterns seem to have emerged.

[6] Data of years after 2008 are all dropped from the figure because they make either ξ less than one or the Gini coefficient greater than one.

The effects of δ_E and $\overline{h}$ on each of the three inequality indices, documented in Tables 6 and 7 are similar in magnitude, respectively, whereas λ, τ and $s_I = s_E$ affecte the bottom 40% income share more in the sense that the magnitude of their impacts on the bottom share is about twice as large as the top 1% income share and the Gini coefficient. How do we interpret these results? To explore those questions, we group those parameters (except λ) into two. One group consists of δ_E and $\overline{h}$ capturing an aspect of a declining business dynamism in the U.S., and another group of τ and $s_I = s_E$ consists of changing fiscal policy measures.

A declining business dynamism is characterized by a falling pace of startups and new businesses with an increasing share of older firms. As Acemoglu *et al.* (2018) argue, it would lead to adverse impacts on growth and productivity because it means a slower pace of reallocation of resources from less efficient to more efficient businesses. To the extent that new firms' innovations, involving job creation and destruction, are important to productivity growth, a declining business dynamism, observed in the U.S. at least since 1980, is a serious concern to policy makers.[7] Evidently, data show that an incentive for new firms to enter the market declined. In particular, according to Decker *et al.* (2014), a declining business dynamism is observed in almost all sectors and all geographic regions, though variations exist.[8] Whatever factors working behind the phenomenon, it is captured by a falling δ_E and $\overline{h}$ in our model. To assess the contribution of a declining business dynamism to the X inequality relationship, let us apply the method used above. That is, we fix those two parameters at the 1981 level and change others. The results are shown in Column (7) of Tables 6 and 7. The magnitude of the impacts are certainly large. However, compared with δ_E, an increase in the magnitude is not particularly dramatic. In addition, the magnitude even slightly fell for the bottom 40% income share. What it suggests is that δ_E and $\overline{h}$ have a relatively large "substitutability" in explaining the X inequality relationship, especially for the bottom income share.

Let us turn to the fiscal policy τ and $s_I = s_E$. Akcigit and Ates (2023) consider changes in the fiscal policy as a possible cause for a declining business dynamism because they are pro-incumbent and reduced knowledge diffusion between leading and lagging firms in technology. According to the study, the U.S. went through major tax system overhauls in the 1980s with a substantial reduction of a statutory corporate tax rate. They also showed that an effective tax rate, which takes into account various tax benefits and determines actual tax bills, also dramatically fell. Akcigit and Ates (2023) also consier an increasing intervention in supporting R&D in the period. The US government began a federal R&D tax credit in 1981, and in the next year state-level support started in Minnesota and spread to other states. Major recipients were incumbent firms because taxable profits were needed for the tax credit. In order to quantify their contribution to the X inequality relationship, τ and $s_I = s_E$ are held fixed at the 1981 level, letting other parameters change. Consider Column (8) of Table 6 first. The magnitude increases nearly in a linear way in the sense that summing the numbers in (5) and (6) approximately gives the magnitude in Column (8). In Table 7, on the other hand, the result is more dramatic because of the cumulative nature of the index Ω_2. The number in (8) is nearly twice as large as the sum of (5) and (6). In this

[7] Startup firms account for about 20 percent of total job creation (see Decker, Haltiwanger, Jarmin and Miranda (2014)).

[8] As factors that are not sector-specific and region-specific, Decker *et al.* (2014) suggest regulation increasing adjustment costs (e.g.Gutiérrez, Jones and Philippon (2019)) and technological progress plus globalization favoring big businesses. Decker, Haltiwanger, Jarmin and Miranda (2016) refer to network externalities which work in favor of big firms, and Akcigit and Ates (2023) argue that a slower knowledge diffusion from frontier firms to lagging firms is a possible cause. Astebro, Braguinsky and Ding (2020) report that an increasing burden of knowledge in R&D and management discouraged startups, again favoring big firms, while population growth slowdown is cited as an important factor in Peters and Walsh (2019).

sense, those policy measures are "complimentary" and their changes appear to reinforce the effects of the other .

Given the above discussion, two results stand out. The effect of a declining business dynamism seems to have generated a larger impact on the Gini coefficient than the fiscal policy changes, though their impacts are comparable when the cumulative index Ω_2 is used in Table 7. Second, Column (9) shows the ratio of (7) over (8). It indicates that the top income share is more affected by a declining business dynamism, and the bottom income share by the policy changes. In this sense, the two factors operated on different aspects of inequality to a different degree.

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