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Diverging Paths: Is Growth Really So-low in Colombia and so High in China?

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Countries:	China & Colombia
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Abstract

Using macroeconomic data from 1952 to 2019, we examine long-term growth in Colombia and China through the lens of multiple models. After running a regression until 1980 for both countries, we find that Chinese GDP rose above its trend, whereas Colombian GDP fell behind. The Solow model mostly confirms our hypothesis that China experienced a positive growth effect, whereas Colombia experienced a negative level effect. Romer is ineffective at explaining growth given the inapplicability of some of its assumptions. We conclude with the finding that under a welfare approach, Colombia actually surpasses China even considering its stagnation in growth.

Keywords— Economic Growth - Total Factor Productivity - Labour Productivity - Exogenous Growth - Endogenous Growth - Welfare

1 Introduction & Methodology

This report examines the economic growth dynamics of China and Colombia from 1952 to 2019. It begins with an explanation of methodology in this section and follows with descriptive statistics of the data gathered on China and Colombia in Section 2. Sections 3, 4 and 5 explore the application of various growth models to our data; namely, the Solow model, a model of TFP and labour productivity, and the Romer model. The report concludes in Section 6 with a discussion of welfare that puts into perspective conclusions drawn only from GDP performances.

Methodology

Historical data supports the assumption that Gross Domestic Product (GDP) per capita generally follows exponential growth with a constant growth rate, making the logarithmic transformation of GDP per capita linear (Groth et al., 2010). We confirm that China and Colombia approximately follow this trend from the early 1950s until 1980 by observing the log(GDP per capita) (hereafter referred to as log(GDPPC)) time series (Figure 1). Estimating an exponential linear regression model for output and output per capita, we analyse deviations from the trend line through different growth models. Output for country i at time t is given by:

$$y_{i,t} = y_0 e^{gt+u_{i,t}} \tag{1}$$

Which, taking logs, becomes:

$$\ln(y_{i,t}) = ln(y_0) + gt + u_{i,t} \tag{2}$$

We run a regression of log(GDP) and log(GDPPC) from 1952 to 1980 in China and 1960 to 1980 in Colombia, informed by the following context. China was ruled by Mao Zedong between 1949-1976 under communist tenets which eventually constituted the Cultural Revolution (Mason, 1984). Following Mao's death, the country radically changed and employed policies such as the 'Four Modernizations' (Jain, 2024). These policies, not properly enacted until 1979, targeted economic rejuvenation in agriculture, industry, science and technology, and defence. 1952–1980 is therefore a uniform period over which to run the regression, and to which the effects of liberalisation after Mao can be compared. The 1980s were also a period of change for Colombia when it faced a combination of the Latin American Debt Crisis, inflation, rising raw material prices, and rising criminality (Cárdenas, 2007). We omit 1952–1960 from our regression because Colombia traversed a 10-year civil war between its Conservative and its Liberal Party until 1958 (Bailey, 1967). 1960–1980 stands out as an appropriate baseline period of stability between periods of turmoil.

After running these regressions, we perform a standard growth accounting exercise to study what drives long-run growth in our countries. We calculate compound annual growth rates (CAGR) over 10-year periods coinciding with decades from the 1950s until 2010s. Decadal growth is informative for long-run trends, since data can better reflect structural changes in the factors of production. Over each subperiod, we break down GDP growth across production inputs using the following Cobb-Douglas production function[1]:

$$Y_{i,t} = A_{i,t} K_{i,t}^{\alpha} (hL)_{i,t}^{1-\alpha}, \quad \text{where} \quad 0 < \alpha < 1 \tag{3}$$

[1] where i and t denote country and time, respectively, Y represents output, A represents total factor productivity (TFP), K represents the physical capital stock, h is the human capital index, L represents the number of employed people, and α represents capital's share of income.

2 Descriptive Statistics

Figure 1: Log(GDP) with estimated trends for China (left) and Colombia (right)

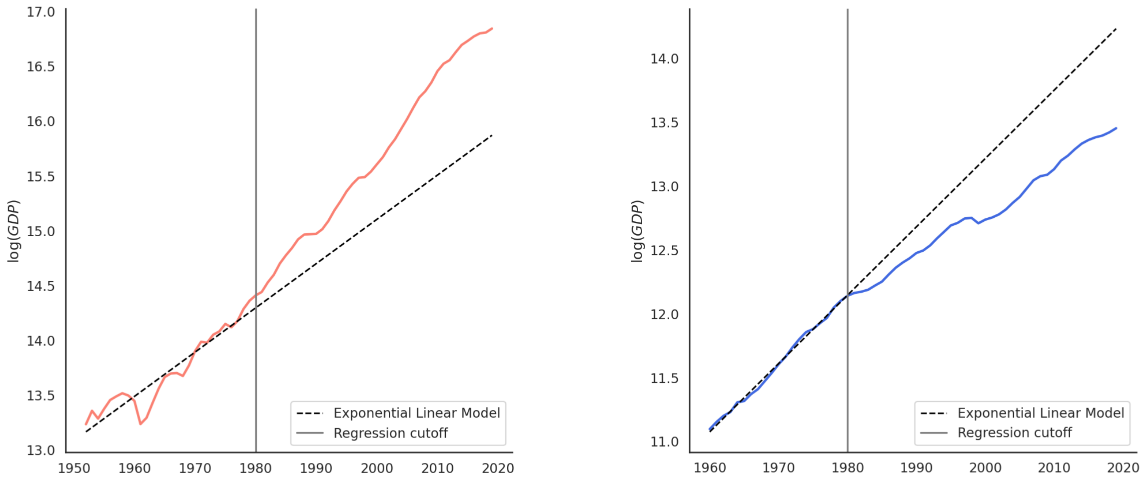


Figure 1 plots China's and Colombia's log(GDP) over time against their respective 1952-1980 and 1960-1980 exponential linear regressions. Both are upward sloping throughout the sample. China's growth is higher from 1980-2010, after which it slows down. Colombia's growth falls after 1980 as output falls below the trend. Its growth then increases and becomes almost parallel to its trend.

Figure 2: Log(GDPPC) with estimated trends for China (left) and Colombia (right)

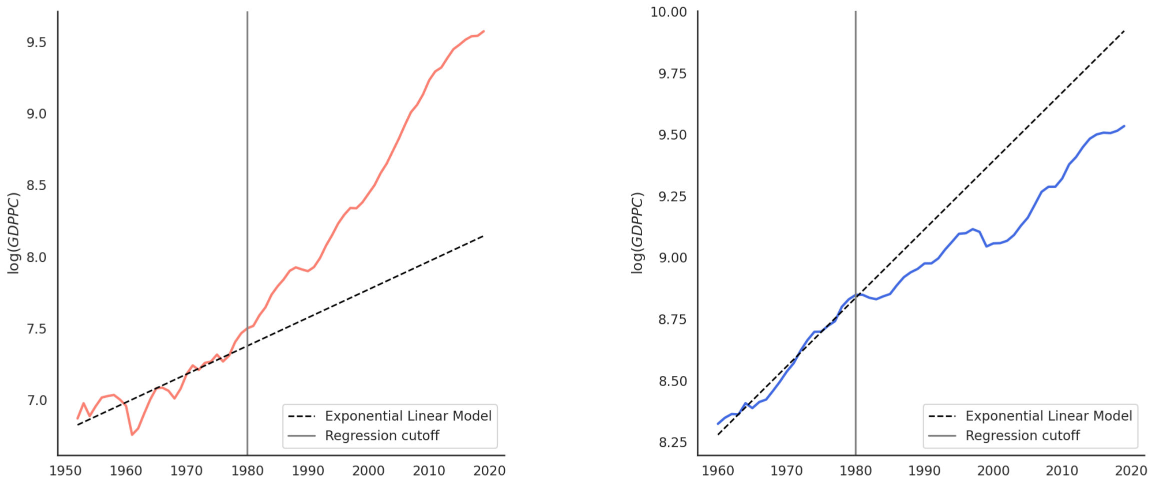


Figure 2 plots China's and Colombia's log(GDPPC) over time against their respective 1952-1980 and 1960-1980 exponential linear regressions. Both China and Colombia's series resemble that of the aggregate graphs. China's per capita deviation is more pronounced than on the aggregate level. Colombia's log(GDP) per capita is more parallel to its trend post-2000 than log(GDP) is.

Figure 3: China Growth Accounting over Decades (1952-2019; $\alpha = 0.3$)

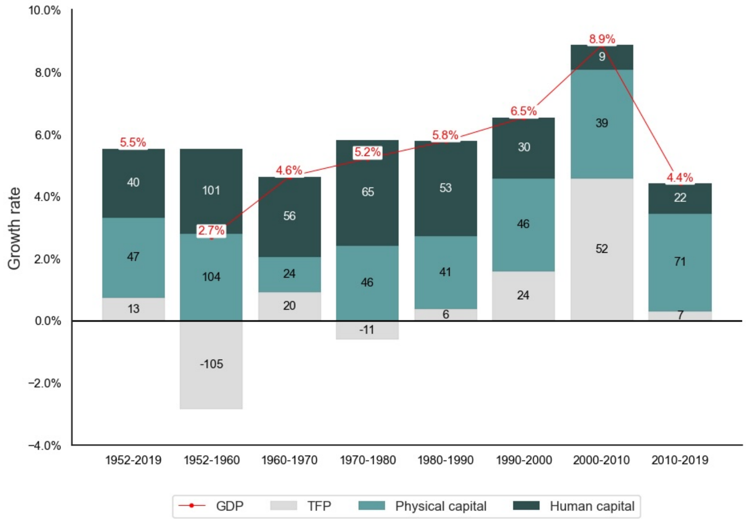
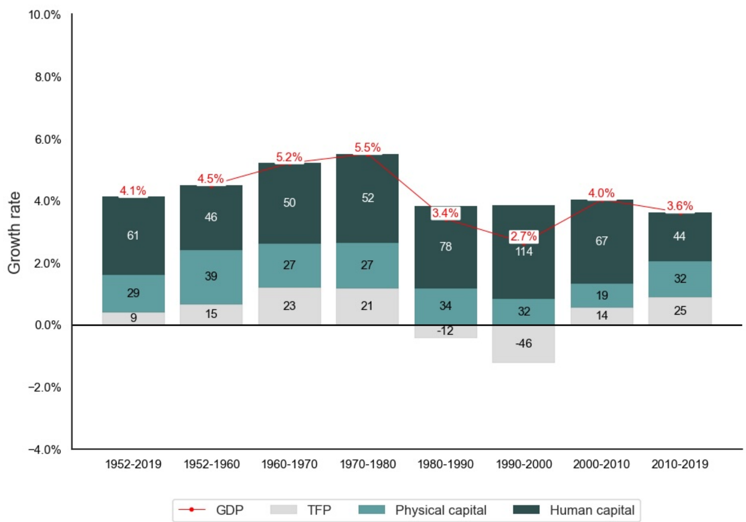


Figure 3 plots growth accounting for China's GDP[2]. Aggregate growth was volatile from 1950s to 1970s, with the main contribution coming from labour. This reflects the largely agricultural make-up of the economy (Chan, 2001). The next three decades display a steady increase in GDP growth, going from 5.8% (annual) in 1980s to 8.9% in 2000s. Growth mainly stems from increasing contributions of capital and TFP (from under 10% in the 1980s, to over 50% in 2000s). This shift coincides with an increasing average savings rate (Figure 7) and strong investments in infrastructure (Jiang et al., 2022). Over the past decade (2010s), we see GDP slowing down, falling to 4.4% annual growth, driven mainly by a decline in annual TFP growth. The observed volatility in Chinese TFP could have many causes, as will be elaborated upon in Section 5. Overall, we see an average annual growth of 5.5% over the whole sample (1952-2019), with labour accounting for about 40%, capital for about 50%, and TFP for about 10%.

Figure 4: Colombia Growth Accounting over Decades (1952-2019; $\alpha = 0.3$)



[2]The Growth accounting conducted in this section utilises a fixed input-mix with a capital share of production $\alpha = 0.3$. For growth accounting with actual empirical estimates, see Section B: Robustness Checks. Actual values for α are closer to 0.41 and 0.52 for China and Colombia, respectively.

Figure 4 plots growth accounting for Colombia's GDP. We see sustained growth in the first three decades of our sample (1950s-1970s), with compound annual rates between 4.5% and 5.5%. In the two decades that follow (1980s-1990s) growth slows down, as the Colombian economy experiences turmoil through events such as the Latin American debt crisis and narco-terrorism (Remmer, 1990). Major shifts in contributions during this time come from TFP - which drops significantly - and from labour, whose contribution towards aggregate output increases steadily. From 2000 to 2019, income growth picks up again, alongside an increased contribution from the capital stock (from 19% to 32% of aggregate GDP growth) and TFP (from 14% to 25% of aggregate GDP growth). Part of this growth correlates with the recent push towards greater ICT investments (Castillo & Vonortas, 2023). Overall, we see an average annual growth of 4.1% over the whole sample (1952-2019), with labour accounting for about 60%, capital for about 30%, and TFP for about 10%.

As a robustness check, we also consider additional explanations of long-term output growth. Since Solow and Romer model GDP from the production side, we consider GDP from the expenditure side, using the equation:

$$Y = C + I + G + (X - M) \tag{4}$$

Where government expenditure (G) and Net Exports ($X - M$) are important drivers of GDP (Y), otherwise neglected. Figure 5 and Figure 6 show the lack of their explanatory value in Colombia, where Net Exports over time are essentially just noise and the post-1990 rise of government expenditure explains a boost in GDP, rather than its observed fall. China's Net Exports are similarly unproductive given their growth lags GDP's 1980 departure from trend. Government expenditure's share in China rose until 1980 when GDP per capita rose past its trend, indicating the possibility of government expenditure as a contributor to growth in China. However, the bulk of the graphs deny the usefulness of government expenditure and net exports.

Figure 5: Log(GDP) and Share of Gov't Expenditure for China (left) and Colombia (right)

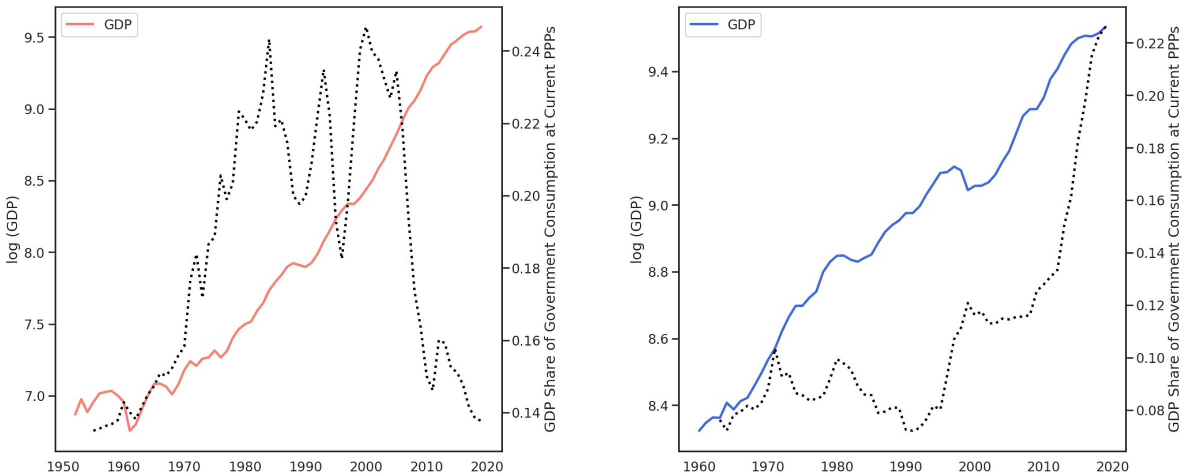
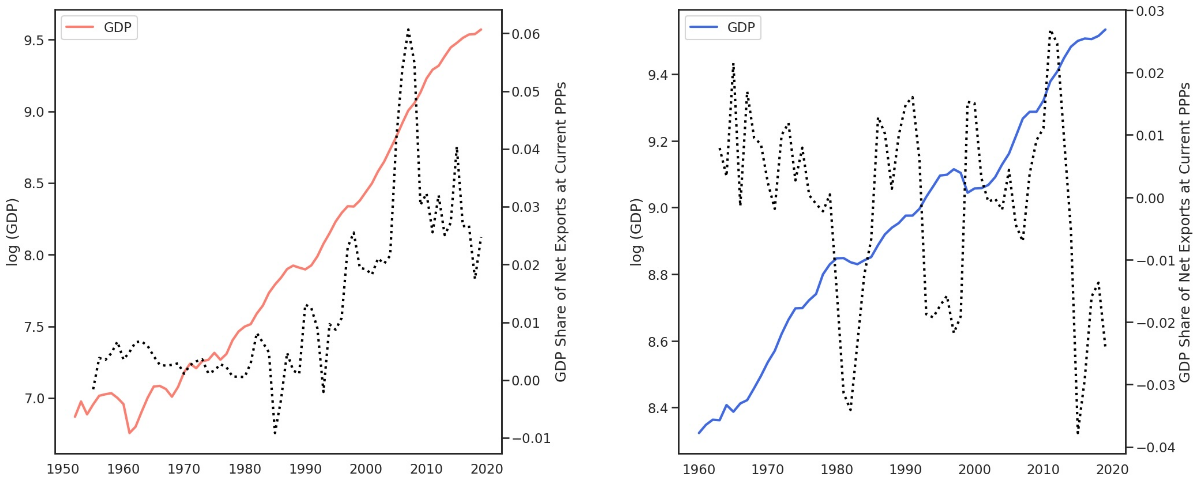


Figure 6: Log(GDP) and Share of Net Exports for China (left) and Colombia (right)



3 The Solow Model

Using data on savings and depreciation, plus our own calculations of TFP and population growth rates, we test implications of Solow. Ultimately, Solow explains how China has raised and then sustained its growth by increasing its savings rate, and more recently its TFP. Simultaneously, the model explains how Colombia's temporarily falling TFP between 1980 and 2000 brought the country's GDP and GDP per capita on a lower growth path.

The Solow model makes two key predictions: firstly, capital accumulation drives growth in the short run, and secondly, diminishing marginal returns on capital require technological progress to sustain growth in the long run. Given the production function in (3), the following equations capture these claims:

In aggregate terms:

$$\ln(Y) = \ln(A) + \alpha \ln(K) + (1-\alpha)\ln(hL) \tag{5}$$

In per worker terms:

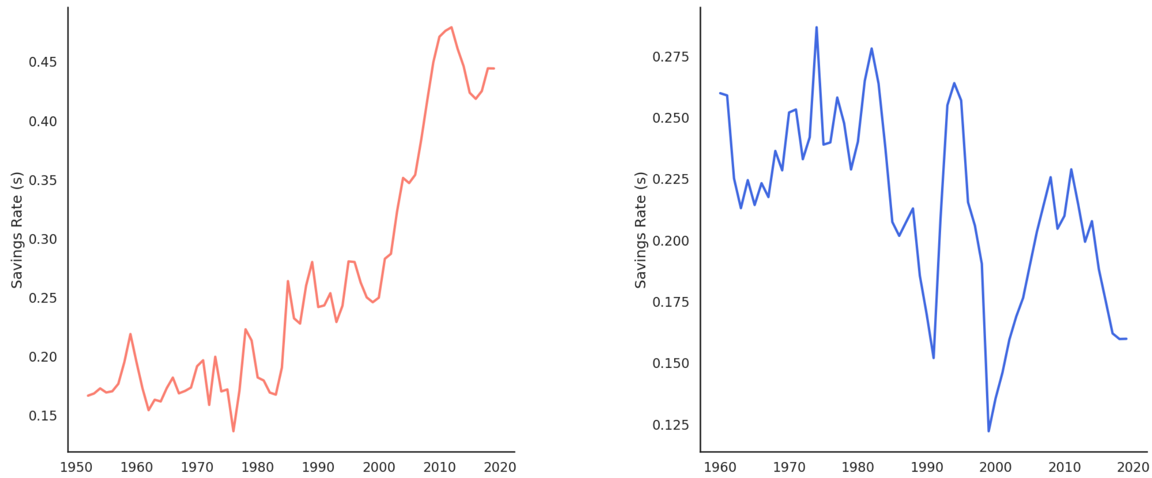
$$\ln(y) = \ln(\frac{Y}{L}) = \ln(A) + \alpha \ln(k) + (1-\alpha)\ln(h) \tag{6}$$

Where:

$$\dot{k} = sAk^{\alpha}h^{1-\alpha} - (\delta + n)k \tag{7}$$

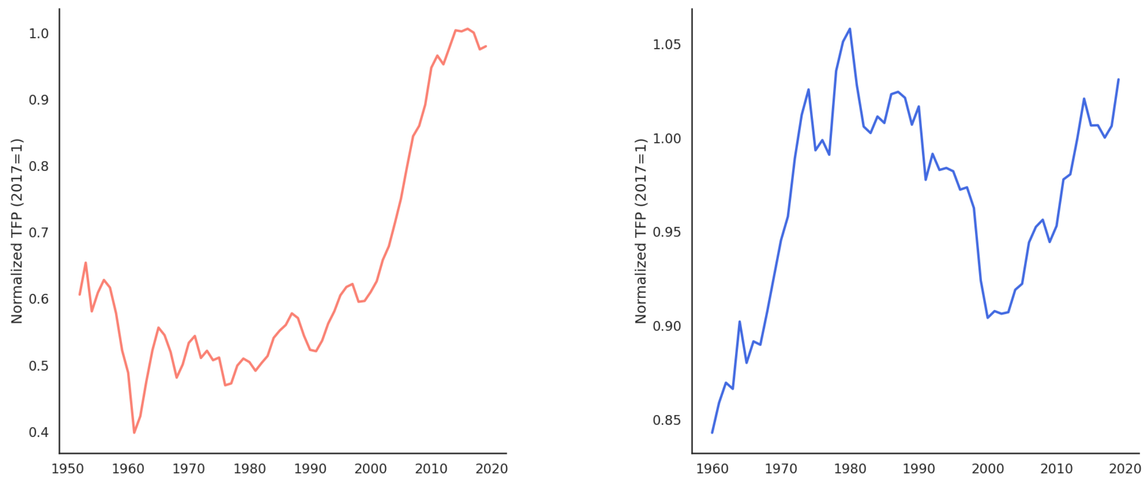
We first analyse individual variables in our data that influence growth in the Solow model, and then draw conclusions on how much the model explains GDP trends observed in Figure 2.

Figure 7: Savings Rate s for China (left) and Colombia (right)



In Solow, the savings rate induces capital accumulation, which raises GDP outcomes. In the data (Figure 7), both countries face a stagnant savings rate prior to 1980. After 1980, China's savings rate rises until 2010. This coincides with the upward deviation of both Chinese GDP measures from their trendlines and supports Solow's emphasis on savings to accumulate capital and generate growth. The Colombian savings rate illustrates the flip side of that: it trends downwards post-1980, which also coincides with Colombian GDP measures deviating downwards from their trends. Note that China's savings rate increases more post-1980 than the Colombian savings rate falls. Indeed, China's savings rate increases by roughly 200% between 1980-2019, while the Colombian savings rate falls 40%. China's GDP measures also deviate more from their trend lines than the Colombian measures do. Therefore, the magnitude of savings rate changes is proportional to GDP deviations, as predicted by equations 5, 6 and 7.

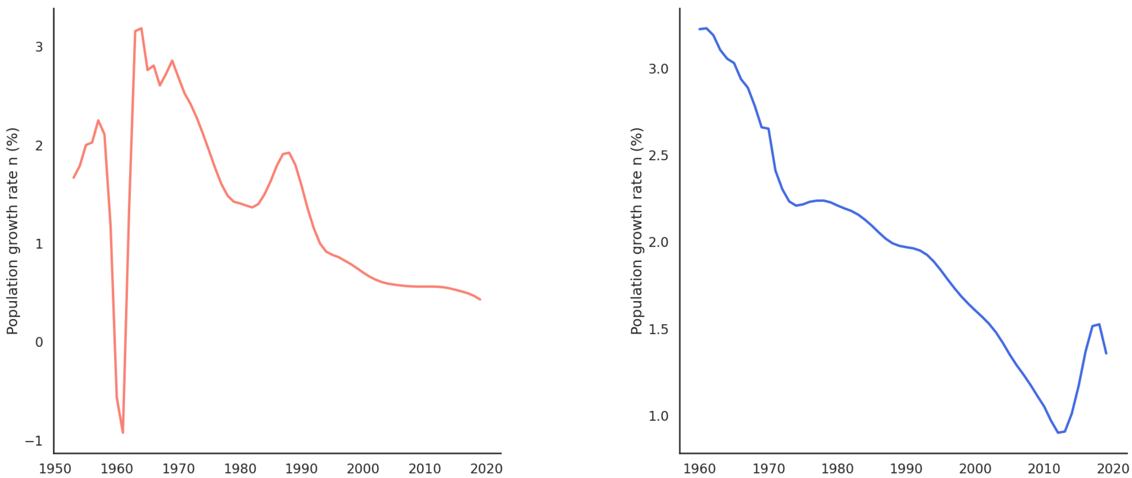
Figure 8: Total Factor Productivity (TFP) for China (left) and Colombia (right)



As in Equation 7, Solow shows increasing TFP also induces capital accumulation. Before 1980 (Figure 8), China's TFP is slightly falling while Colombia's rises. However, China's TFP rises after that and specifically bursts around 2000. This generally mirrors the increase in GDP growth and explains how China sustained its growth in the long run. By contrast, Colombia's TFP falls between 1980-2000, before rising again similarly to pre-1980. Again, this justifies a temporarily lower growth in GDP outcomes post-1980. Moreover, the rise in TFP after 2000 correlates with GDP becoming almost parallel to its trend line. The growth accounting exercise (Figure 12) illustrates this by showing how GDP growth is 0% between 1980-2000, while it nears 2% for both 1960-1980 and for 2000-2019.

Figure 9: Depreciation Rate d for China (left) and Colombia (right)

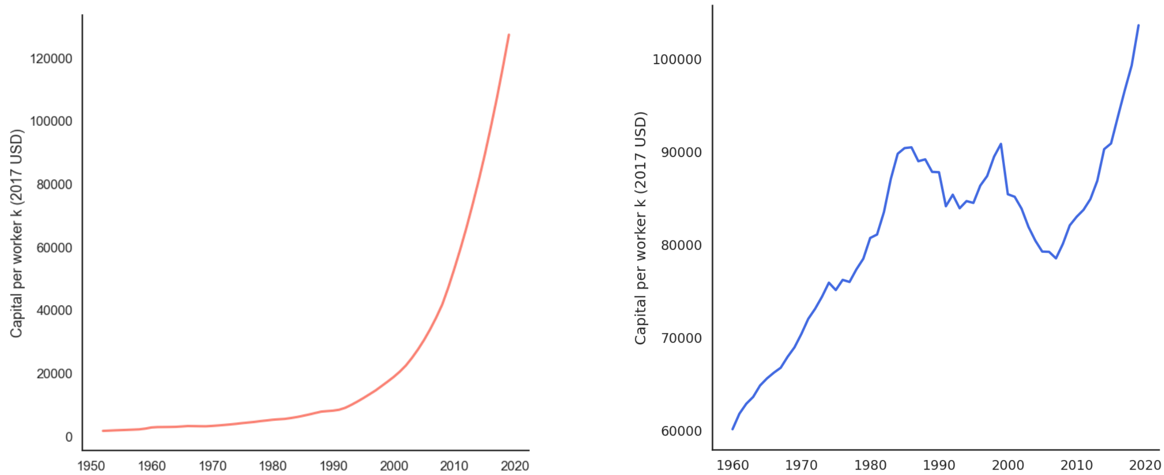
Figure 10: Population Growth Rate n for China (left) and Colombia (right)



The depreciation and the population growth rates in our data (Figure 9 and Figure 10) are less insightful. Interestingly, Colombia's depreciation rate rises except during the period where GDP growth falls. This challenges the Solow model, in which a rising depreciation rate should reduce GDP growth (equation (7)).

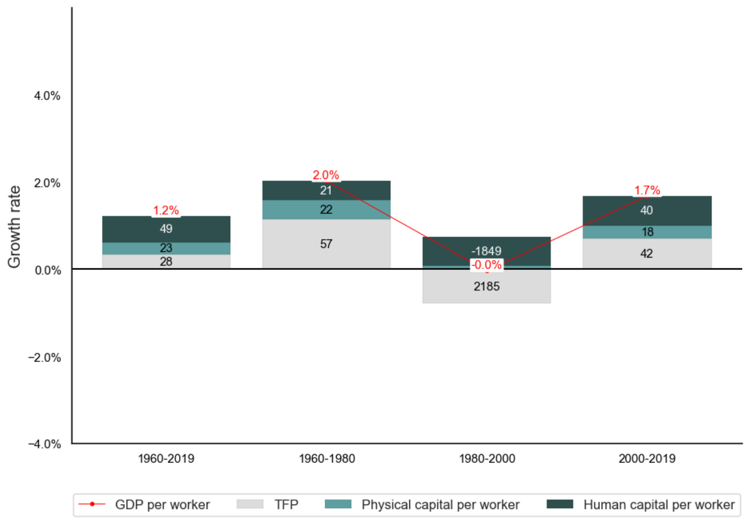
Likewise, both countries face a falling population growth rate post-1980, which Solow predicts should drive the growth of GDP per capita upwards and of GDP downwards. This is the case for neither country: both have GDP outcomes that move in pairs.

Figure 11: Capital per Worker k for China (left) and Colombia (right)



We conclude that between 1952-1980 China is in a steady state, where capital per worker growth is miniscule (Figure 11 and equation 7). China then experiences a growth effect at the same time as the liberalization policies of the 1980s: its rising savings rate and then soaring TFP enable it to grow at a faster rate and sustain this change. Using the Solow lexicon, China has successfully been raising its steady state such that the capital production (and capital growth) defined in equation 7 is never zero. Note that China has been drawing its growth from both TFP and savings rate increases (Figure 3). However, it cannot increase its savings rate forever. Perhaps our sample is not large enough to observe this limit. Nevertheless, the slight stagnation in GDP growth post-2010 hints that the savings rate has little remaining growth-inducing power. The Solow model then predicts that China will need TFP growth in the near future to remain on its current growth path. On the other hand, Colombia seems to experience a negative level effect post-1980: its growth is temporarily hindered by an important fall in TFP (Figure 12), which subsequently grows once more and brings GDP measures parallel to, yet below, their original trend lines (Figure 2). For this to make sense, changes in Colombia's depreciation rate must be outweighed by changes in TFP; otherwise, the data undermines Solow's predictions. Overall, our application of the Solow model emphasises the importance of TFP in growth.

Figure 12: PC Growth Accounting in Colombia over 20-year splits (1960-2019; $\alpha = 0.3$)



4 TFP & Labour Productivity

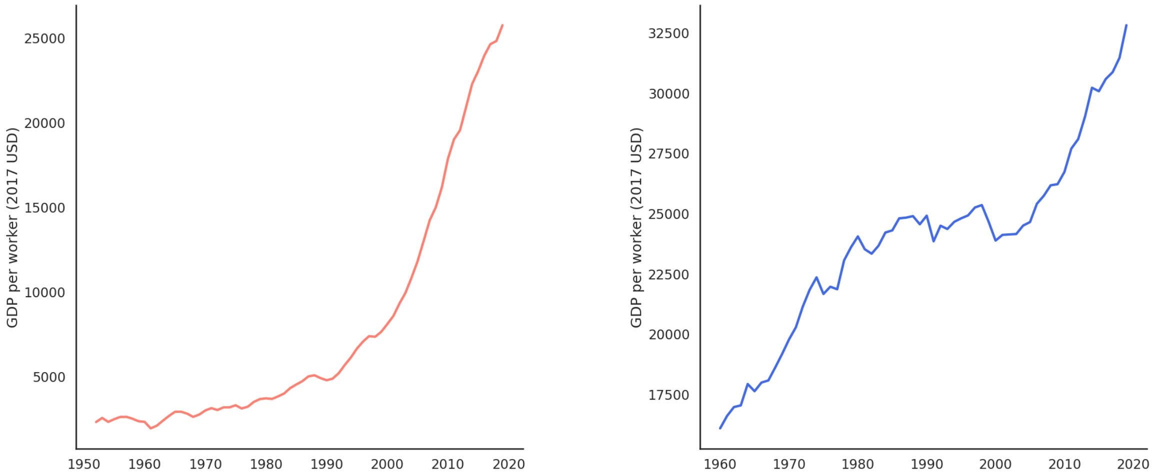
TFP and labour productivity (LP) are different productivity measures. TFP is a residual from the production function after accounting for pure contributions of capital and labour. LP is ultimately a measure of output per worker ($\frac{Y}{L}$): how much output is generated per employed individual. It is measured by dividing GDP by the number of employed workers. LP and log(GDP) per capita should thus move in pairs, which we observe this in the data (Figure 13).

While the two measures often correlate, there is not necessarily a positive relationship between TFP and LP. To illustrate, consider an economy that invests more than it loses through depreciation, and thus increases GDP via capital. Simultaneously, the number of workers remains constant and LP hence rises. However, TFP can remain unchanged. Although unrealistic, this example shows that one productivity measure can rise while the other does not.

In our data, LP and TFP (Figure 13 and Figure 8) generally rise in both countries over 1952-2019. China displays a nicely convex increase in both TFP and LP from 1980 to 2010. However, TFP stagnates after that, while LP shows no sign of stagnation. For Colombia, TFP and LP both increase from 1950-1980 and from 2000-2019. However, TFP falls significantly between 1980-2000 while LP simply stagnates. While both measures tend to move together in the long run, the relationship between them is not one-to-one.

Both countries' rising LPs are consistent with their rise in human capital per worker Figure 15. This may contribute to the rise in LP, and also explain why, when TFP falls for Colombia, LP only stagnates as it is offset by rising human capital. The generally rising LPs also correlate with sectoral shifts away from agriculture associated with labour productivity increases from wage increases Chan (2001). The latter assumes wage can serve as a proxy for productivity, as in Feyrer (2008). As stated above, the capital accumulation discussed in Section 3 explains why China, which has benefited from a deepening capital stock, has observed a rise in LP not necessarily reflected in TFP. This supports the much smoother increase in the country's LP relative to its TFP which fluctuates significantly as it grows.

Figure 13: Labour Productivity (LP) for China (left) and Colombia (right)



5 The Romer Model

Long-term output trends show sustained growth in the late 20th century. The two countries grew roughly 6% (China) and 4% annually (Colombia) from 1950 onwards. Clearly, the diminishing returns that the Solow model warns of are somehow overcome. This supports Romer's endogenous growth, which explains long-run growth as the result of technology improvements, captured by TFP increases. The main driver of TFP growth is population, which contributes positively to both aggregate and per capita output growth. In the model, the aggregate stock of ideas evolves according to[3]:

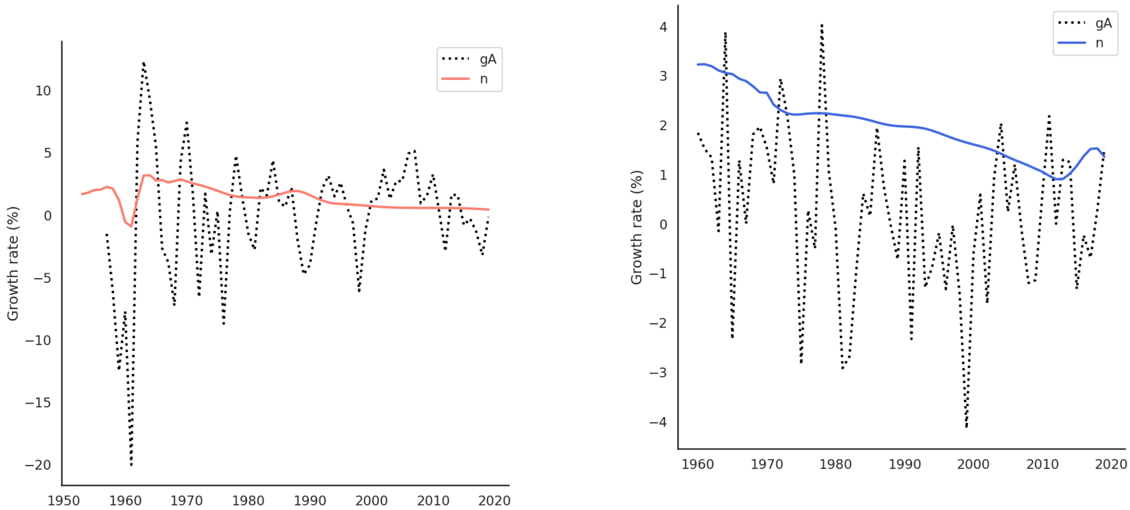
$$\dot{A} = \theta L_A^{\lambda} A^{\phi} \quad \text{where} \quad 0 \leq \lambda \leq 1 \quad \text{and} \quad 0 \leq \phi < 1 \tag{8}$$

where L_A is the number of researchers. Assuming L_A is a constant fraction of population, A grows as long as population growth is positive, ceteris paribus. Furthermore, while growth in human capital strains per capita output in the Solow model by requiring more capital to maintain a constant output per worker in the face of diminishing returns, Romer suggests that population (i.e., positive n) fuels the production of ideas, and hence growth in TFP. Generally, the growth of A can be described by the following equation:

$$g(A) = \frac{\dot{A}}{A} = \theta L_A^{\lambda} A^{\phi-1} \tag{9}$$

[3]Where: λ represents the effectiveness of researchers, often referred to as the stepping-on-toes effect; ϕ determines whether research productivity increases with A; θ represents the productivity residual of idea production.

Figure 14: $g(A)$ and n in China (left) and Colombia (right)



Which, on a balanced growth path, indicates:

$$g(A) = \frac{\lambda}{1-\phi} n \tag{10}$$

Barring the fact that TFP displays volatility in Figure 14, both China and Colombia appear to be on a balanced growth path befitting the Romer growth description[4].

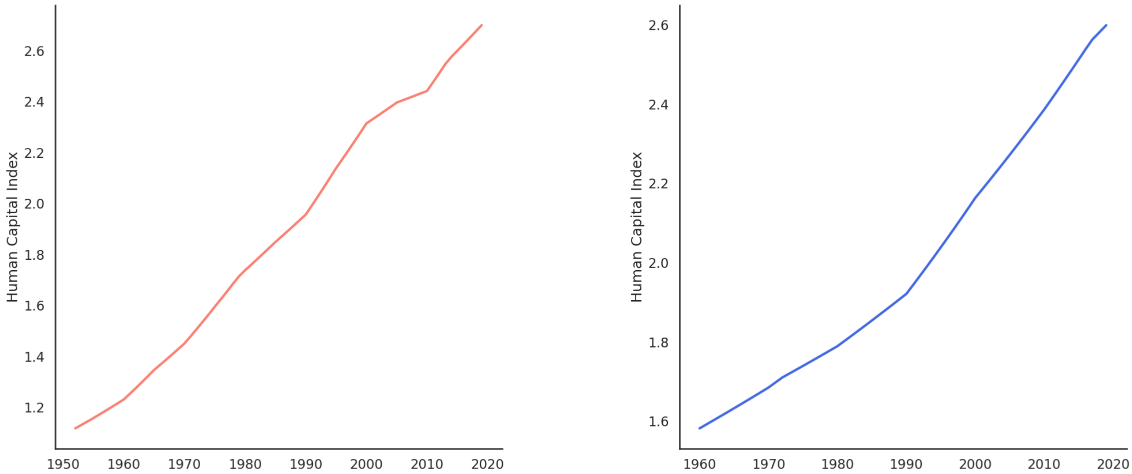
Assuming equation (10) holds and that ϕ and λ are constant, a change in A would require a change of the same magnitude in θL_A for g(A) to remain on a balanced growth path.

We observe this with China: with an ever-increasing stock of ideas from Figure 8, θ and L_A have to cumulatively off-set this increase for TFP growth to remain constant . This hypothesis finds further support given the number of researchers increased (OECD, 2024) – increasing L_A – and the human capital index grew from a value of 1 (1960) to above 3 (2019) in Figure 15, almost a threefold increase over six decades – which translates to higher θ. For Colombia, this is not the case Figure 8, so it would be out of our scope to fit the data we see within the Romer framework.

Upon second inspection, another question arises: is this model even applicable to our data? A key assumption of this model is that researchers are given intellectual property rights as an incentive to innovate. That is, ideas are subject to a positive externality of production due to their non-rivalrous nature, ensuring their under-provision by the market if unprotected. Using patents granted as a proxy for protection of intellectual property rights, WIPO (2022) shows that neither Colombia nor China possessed a solid patent system until at least the 1990s. The graphs seemingly supporting Romer's growth dynamics pre-1990 could thus be spurious correlations. For instance, patents granted in China were practically zero until 2000. In effect, TFP was as high in 1952 as it was in 2000, but then abruptly exploded. Although data is limited, Chinese

[4] One would (ex ante) expect the growth of TFP measure to be noisy, as TFP is affected by random shocks in the economy.

Figure 15: Human Capital Index h in China (left) and Colombia (right)



expenditure in R&D has also risen since 1995, after decades of near-zero spending (UNESCO, 2024). Colombia's investment in R&D has increased slightly but is still extremely low. Testing for Romer's crucial assumption on the (partial) excludability of ideas therefore adds nuance to the applicability of Romer to our countries' economic development.

Romer is also better suited to explain growth in advanced (frontier) economies rather than emerging (laggard) economies (Jones & Vollrath, 2013) because technological growth ultimately sustains income per capita growth over time. Nevertheless, if discrepancy in income levels between countries stems only from differing levels of technology, then why do emerging economies not just "copy" ideas from advanced economies? Strictly following the model's set up, this would solve the problem of lagging income levels. Yet, over the period of interest we still observe large income differences between our countries and more developed economies. The Romer model thus loses explanatory power when we discard other factors besides technological growth, one being the quality of institutions in a country. Given this, Romer's predictions about the relationship between population growth and technological innovation are seriously hampered when the assumption of market efficiency is weakened.

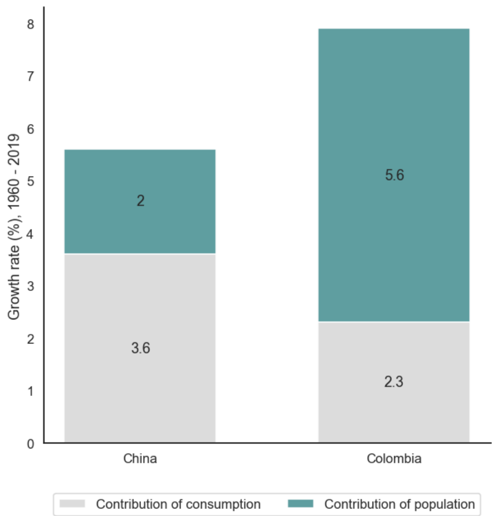
6 Welfare

We follow the approach in Adhami et al. (2023) to assess tradeoffs between population growth and individual well-being. The authors argue per capita GDP is a poor measure of social welfare. Instead, they propose a measure that weighs population growth more than consumption per capita growth:

$$g_\lambda = v(c) \cdot n + g_c \tag{11}$$

We reproduce the authors' calculations for China and Colombia to generate these figures[5]:

Figure 16: Consumption Equivalent Welfare Growth (1960-2019)



Applying this welfare function, Colombia outgrows China even if its GDP PC growth is lower. This is because Colombia maintained a higher population growth (Figure 10) and a high value of life in consumption-equivalent units: 2.9 years of per capita consumption, compared to 1.8 years in China (Table 1). Clearly, Colombia values human life, implicitly accepting a much lower per capita growth rate than China (Figure 16) to ensure more people can profit from economic growth.

[5] g_λ is CE welfare growth; $v(c)$ is the CE value of life and g_c is the growth rate of consumption.

Table 1: Decomposing Welfare growth

	g_λ	g_c	n	v(c)	v(c) $\cdot n$	Pop Share
China	5.6	3.6	1.3	1.8	2.0	36%
Colombia	7.9	2.3	2.0	2.9	5.6	71%

China exemplifies the tradeoff in question, as it favoured individual well-being over population growth. It restricted the latter via the 1979 one-child policy, which explains its relatively lower welfare growth in Figure 16. However, this policy enabled faster capital per capita accumulation, which lifted roughly 800 million people out of poverty. According to the world bank, only about 0.5% of the Chinese population now lives below the international poverty line, compared to about 6.6% in Colombia (WorldBank, 2024). We hold that in the long-run, China's low population growth rate will have a negative impact on individual well-being via its ageing population, for instance by raising health care expenditure and declining the labour force (Du & Wang, 2011). This discussion highlights how solely focusing on GDP growth, as done in the core of this paper, can ignore welfare developments that may ultimately be more meaningful to us.

References

Adhami, M., Bils, M., Jones, C. & Klenow, P. (2023). Population and Welfare: The Greatest Good for the Greatest Number. *NATIONAL BUREAU OF ECONOMIC RESEARCH*, *NBER Working Paper Series*(Working Paper 31999).

Bailey, N. (1967). *La Violencia* in Colombia. *Journal of Inter-American Studies*, *9*(4), 561–575.

Castillo, J. C. & Vonortas, N. S. (2023). TFP, ICT and absorptive capacities: micro-level evidence from Colombia. *The Journal of Technology Transfer*.

Chan, A. (2001). *Mao's Crusade: Politics and Policy Implementation in China's Great Leap Forward* (1st ed.). Oxford University Press.

Cárdenas, M. (2007). ECONOMIC GROWTH IN COLOMBIA: A REVERSAL OF 'FORTUNE'? *DOCUMENTOS DE TRABAJO*, *36*.

Du, Y. & Wang, M. (2011). Population Ageing, Domestic Consumption and Future Economic Growth in China. In J. Golley & L. Song (Eds.), *Rising China: Global Challenges and Opportunities.* ANU Press. doi: 10.22459/RC.06.2011.17

Feyrer, J. (2008). Aggregate Evidence on the Link between Age Structure and Productivity. *Population and Development Review*, *34*, 78–99.

Groth, C., Koch, K.-J. & Steger, T. (2010). When economic growth is less than exponential. *Economic Theory*, *44*(2), 213–242.

Jain, R. (2024). China's Economic Development Policies, Challenges and Strategies, 1978-present. *Indian Journal of Asian Affairs*, *30*(2), 65–84.

Jiang, S., Miao, J. & Zhang, Y. (2022). CHINA'S HOUSING BUBBLE, INFRASTRUCTURE INVESTMENT, AND ECONOMIC GROWTH. *International Economic Review*, *63*(3), 1189–1237.

Jones, C. I. & Vollrath, D. (2013). *Introduction to Economic Growth* (THIRD EDITION ed.). New York: W. W. Norton & Co.

Mason, D. (1984). China's Four Modernizations: Blueprint for Development or Prelude to Turmoil? *Asian Affairs: An American Review*, *11*(3), 47–70. Retrieved 2024-02-27, from http://www.tandfonline.com/doi/abs/10.1080/00927678.1984.10553699 doi: 10.1080/00927678.1984.10553699

OECD. (2024). *'Researchers' (indicator).* Retrieved 2024-02-27, from doi:10.1787/20ddfb0f-en

Remmer, K. (1990). Democracy and Economic Crisis: The Latin American Experience. In (Vol. 3, pp. 315–336).

UNESCO. (2024). *Research and development expenditure (% of GDP).* Institute for Statistics (UIS). Retrieved 2024-02-27, from https://data.worldbank.org/indicator/GB.XPD.RSDV.GD.ZS?locations=CN

WIPO. (2022). *World Intellectual Property Indicators 2022.* Geneva: World Intellectual Property Organization. (OCLC: 1357528376)

WorldBank. (2024). *Poverty headcount ratio at $2.15 a day (2017 PPP) (% of population).* Retrieved 2024-02-27, from doi:10.1787/20ddfb0f-en

A Appendix

Figure 17: Per Capita Growth Accounting in China (1952-2019)

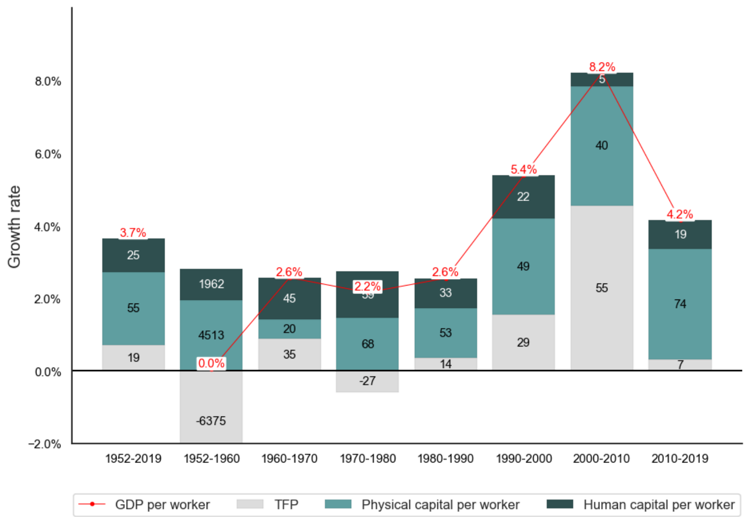


Figure 18: Per Capita Growth Accounting in Colombia (1960-2019)

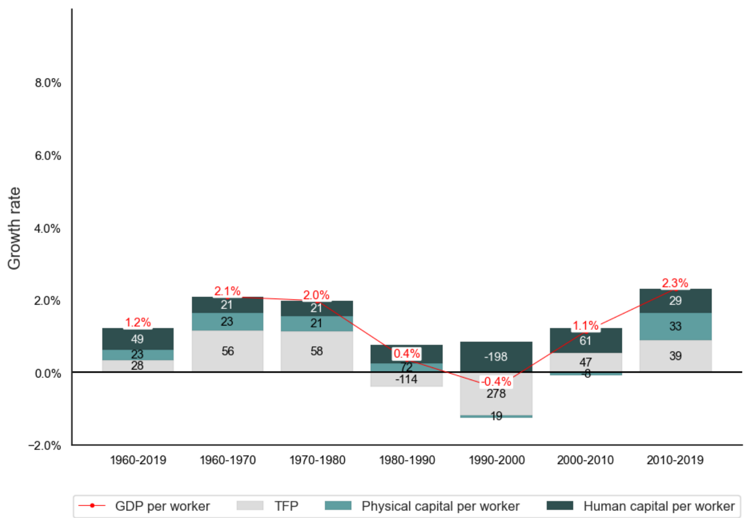
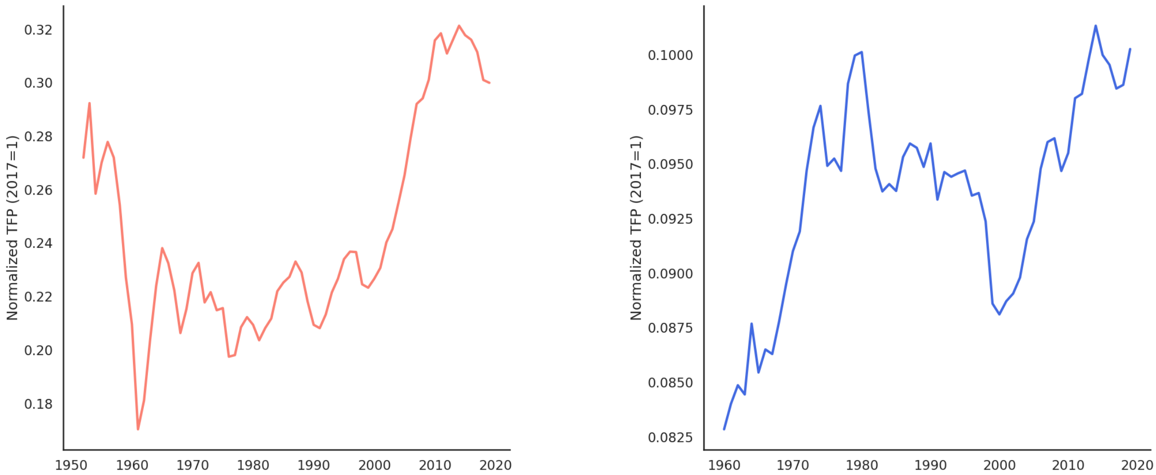


Figure 19: TFP with α_{China}= 0.41 (left) and $\alpha_{Colombia}$= 0.52 (right)



B Robustness Checks

Figure 20: China Growth Accounting over Decades (1952-2019; α = 0.41)

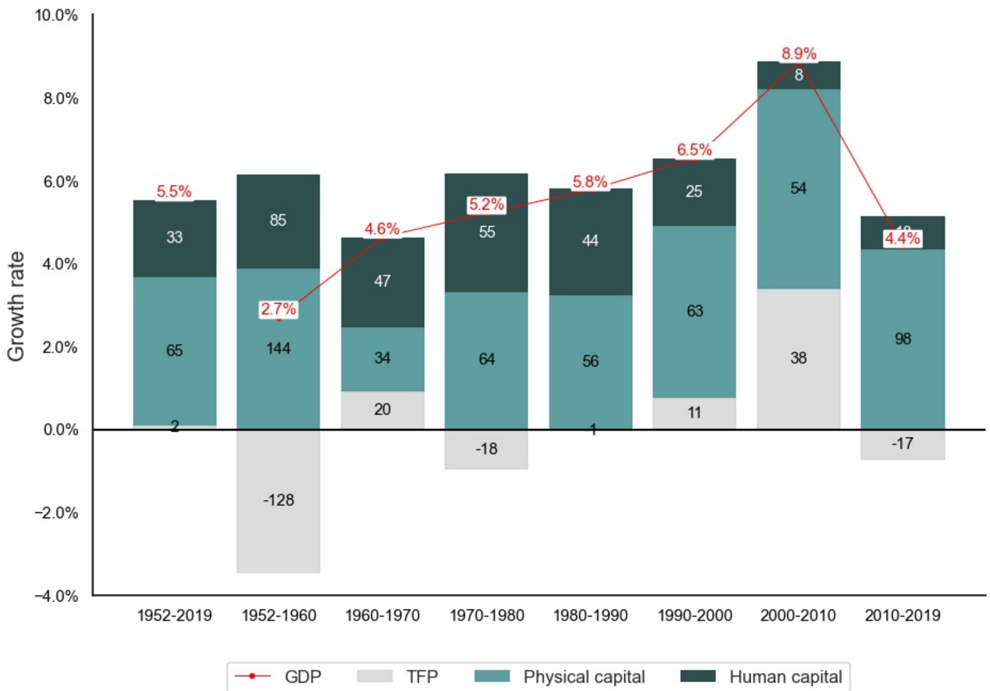


Figure 21: Colombia Growth Accounting over Decades (1952-2019; $\alpha = 0.52$)