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Will China Avoid Japanification? An Empirical Analysis of China's Total Factor Productivity Growth Determinants at the National and Provincial Level

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Abstract

This paper contributes to the literature on the “Japanification” of China by computing updated estimates of Total Factor Productivity (TFP) growth at the provincial level in China from 1992 to 2022 and by using a TWFE panel regression to analyse its key determinants. It then provides a descriptive comparison with literature and data on the 1990s Japanese TFP growth collapse. This aims to help answer whether China is likely to face a similar scenario of long-term near-zero growth. We find that TFP growth in China has slowed, and convergence to the technological frontier and capital misallocation are consistent determinants that could explain such slowdown, as was the case for Japan. This points to a substantial risk of “Japanification”, but China and Japan retain sufficient differences such that certain policies could enable China to avoid a “Lost Decades” scenario.

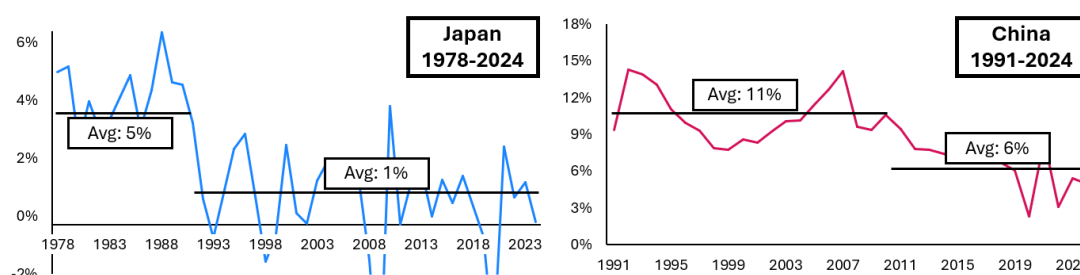
Keywords: China, Japan, TFP Growth, Total Factor Productivity, Capital Misallocation, Japanification, Growth Accounting, Solow Residual

1. Introduction

Both China and Japan have experienced a sharp slowdown after a “miracle” growth period. Japan recorded average annual GDP growth of 9% from 1961–1973, a slower yet robust 4% from 1974–1991, and near-zero growth from the early 1990s to the present. China grew on average by 10% from the 1978 Reform and Opening Up to 2010, but since then, growth has slowed to a new average of about 6% (World Bank, 2026).

China's annual growth rate will likely continue to decline as the economy matures. However, it remains unclear whether it will stabilise around 2–3%, as in many developed economies, or whether the country is heading towards a “Lost Decades” scenario akin to Japan. Modern China and 1980s Japan indeed share many similarities: On the demand side, low inflation, high leverage, and inflated real-estate prices. On the supply side, low population growth, low immigration, diminishing returns to capital accumulation, and diminishing productivity growth. This has prompted recent discussion of a possible “Japanification”, defined as a prolonged period of near-zero growth and deflation, as a threat to China and its 1,400 million population.

Figure 1: GDP Growth in Japan and China (Source: World Bank, 2026)



However, recent research comparing the supply-side factors is scarce, particularly regarding productivity growth. This research aims to provide a two-fold contribution to address this gap: First, it will use a Solow framework to compute updated estimates for Chinese provincial Total Factor Productivity (TFP) growth through 2022, drawing on data from China's National Bureau of Statistics (NBS), existing secondary literature, and 25 provincial statistical yearbooks – many of which are not publicly available. Second, it will construct a Two-Way Fixed Effects (TWFE) panel regression to analyse its determinants and compare them with those highlighted by the Japanese TFP slowdown literature. The paper relies on existing results for Japan rather than conducting a separate empirical analysis; therefore, this comparison remains conceptual. We hope this will help answer whether China is likely to fall into a near-zero TFP growth “Japanification” scenario. The paper seeks to answer the question: How do the determinants of TFP growth we estimate for China during 2000–2022 compare with those identified for Japan during 1980–2000 in the existing literature?

The remainder of the paper is organised as follows: Section 2 reviews related literature. Section 3 discusses data and methodology. Section 4 presents the TFP growth estimates at the national and provincial levels, as well as regressions of TFP growth against various determinants. Section 5 compares the results with Japan and provides policy recommendations. Section 6 concludes.

2. Literature Review

2.1. Theoretical Background on TFP Growth and its Determinants

Modern literature on long-term growth has been built on the seminal work of Solow (1956), who developed a neoclassical model explaining aggregate growth through changes in physical capital, labour and technology. It predicts that, because the returns to capital diminish over time, long-term output growth is determined solely by technology growth and population growth.

The concept of TFP arose from a follow-up paper, where Solow (1957) introduced a way to empirically measure technology growth by subtracting measured growth in capital deepening from growth in income per capita, yielding a technology growth residual. Subsequent literature has refined this method, now referred to as “growth accounting,” and technology change is denoted more broadly as “change in productivity” or change in TFP (Barro, 1999).

However, the Solow model has the key drawback that TFP is treated as exogenous, and therefore it must be measured as a residual. Since the 1980s, economists have attempted to address this problem by creating models that endogenise TFP and by empirically measuring its determinants. The most influential studies have focused on the role of R&D (Romer, 1990; Aghion

and Howitt, 1992), human capital (Lucas, 1988), efficiency in resource allocation (Banerjee and Duflo, 2005), technology diffusion (Eaton and Kortum, 1999) and institutional quality (Hall and Jones, 1999).

In empirical analysis, panel regressions with TFP growth on the left-hand side have been a standard method for measuring TFP determinants, motivating our approach. An early example is Miller and Upadhyay (2000). Kim and Loayza (2019) provide the most compelling modern analysis, aggregating economic indicators into five main determinants (innovation, education, market efficiency, infrastructure, and institutions) from a 100+ country panel over 1985-2015. They find an interesting conclusion: the relative importance of TFP determinants varies across countries, particularly between OECD and non-OECD members. This motivates a comparison between TFP determinants across Japan and China.

2.2. Determinants of TFP Growth in 1980s-1990s Japan

The seminal work of Hayashi and Prescott (2002) uses a neoclassical growth model to argue that firms were not financially constrained for long after the 1991 “credit-crunch” and that, instead, a collapse in TFP growth is the main culprit behind the long-term “Lost Decades” outcome. They suggest this was caused by persistent subsidising of inefficient firms. This study has led to dozens of studies on the determinants of the TFP slowdown.

The majority of papers have focused on inefficient allocation of capital as the core problem. Caballero et al. (2008) argue that insolvent companies (or “zombies”) were kept afloat by subsidised credit from banks, suppressing the normal competitive process. They use firm-level data to show that zombies exhibit lower TFP growth, and they also reduce investment and employment in non-zombies. Moreover, they show that zombies were most common in non-manufacturing industries such as construction and real estate. Indeed, several papers highlighted that construction and real estate received more bank credit than other sectors despite their relative underperformance, provoked by the early 1990s collapse of land prices (Ito and Sasaki, 2002; Fukao, 2000; Hosono and Sakuragawa, 2003). According to Hosono and Sakuragawa (2003), real estate-related and construction loans accounted for 42.4% of all disclosed non-performing credit during this period. Other important studies analysing misallocation of capital at the firm level include Fukao and Kwon (2006) and Nishimura et al. (2005).

Research also analyses the natural exhaustion of catch-up TFP growth as Japan converged with the US. Cameron (2005) estimates a panel regression across 11 industries for 1963-1989. He finds that the productivity gap has a significantly positive and gradually diminishing effect on TFP growth, which can explain the trajectory of Japanese TFP growth and the pattern of increasing R&D expenditures, reflecting a shift toward innovation at the frontier. Comin (2008) similarly finds a deceleration in IT diffusion during the 1990s. Both studies offer meaningful insights but fail to explain the decline in Japanese TFP relative to the US from 1983-1989, as measured by Cameron (2005).

Therefore, the fall in TFP growth seems to have been a combination of a natural process of convergence, aggravated by the Japanese-specific shock of capital misallocation across firms.

2.3. Determinants of TFP Growth in Modern China

Existing papers were mostly published in the 2000s and early 2010s, and can be broadly split between firm-level analyses and provincial data analyses.

The first group uses firm-level data to analyse inefficient allocation of capital among firms. These papers generally find there is substantial capital misallocation across Chinese firms, but almost all studies rely on the Industrial Enterprise Survey from the NBS, which was discontinued in 2013 and is now restricted from the public, so their representativeness for contemporary China is limited (Hsieh and Klenow, 2009; Brandt et al., 2020; Iida et al., 2018).

The second group uses TFP by province to obtain enough observations for a panel regression. An interesting example is Tian and Yu (2012), who collected results from 150 primary studies on TFP growth in China published between 1990-2010 and constructed averages across time periods, regions, and sectors to build a “consensus” picture. They find higher TFP growth in the Eastern region, in the manufacturing sector, and after 1978. A more recent study by Bai and Zhang (2016) used provincial data until 2014 to examine the post-2008 TFP slowdown, arguing that a rising share of production in the tertiary sector and reduced convergence effects due to rising income per capita are the main culprits. Finally, Zhou and Dahal (2024) present the most recent provincial panel data through 2018 and find that, despite the overall slowdown, R&D remains an effective driver of TFP.

The determinants considered in the literature on China are much broader than on Japan. However, similarities are found in the focus on efficient allocation of capital among firms and of convergence to the technological frontier. Therefore, these would be interesting determinants to study.

2.4. Comparative Studies of the Japanese and the Chinese Slowdown

The first branch of research focuses on demand-side comparisons, examining asset valuations, export demand and real estate prices, among others, but they are less directly related to this paper's supply-side TFP framework (Rixtel, 2025; Liu, 2025; Zhao et al., 2017).

We then focus on the second branch of research, making supply-side comparisons: Fukao and Yuan (2016) conduct a Solow-based growth accounting exercise for Japan and China, finding that China compensated for lower TFP growth than Japan during its miracle period by accumulating capital more rapidly, and that this capital now faces diminishing returns. China's demographic headwinds are also worse than Japan's, further aggravating diminishing returns to capital. Therefore, they argue that for China to escape "Japanification", there must be strong TFP growth. However, they do not analyse the determinants of TFP, and their growth accounting is limited to 2010.

In another supply-side analysis, Yao (2016) highlights the role of sub-national convergence in stimulating overall growth, arguing that China's advantage is that it has greater provincial disparity than 1980s Japan: inland provinces have a much lower per capita income, a lower urbanisation share, and a higher share of agriculture than coastal provinces. Finally, Murach and Wagner (2017) compare the development of structural change between China, Korea and Japan. They find that the 2017 Chinese share in each industry is comparable to Japan's in 1978 and exhibits the same trend, moving away from the high-productivity manufacturing sector and towards the low-productivity service sector.

Therefore, whilst there have been some supply-side comparisons of the sources of growth and productivity for Japan and China, to my knowledge, there have been no studies that compute TFP growth and compare its determinants between 1980s-1990s Japan and modern China using post-2010 data.

2.5. Conclusion

Neoclassical growth theory suggests TFP growth is a key factor in long-term output growth, and there has been a large body of literature analysing its determinants. Global studies have found TFP determinants may vary by country. For Japan in 1980s-1990s, misallocation of capital in firms and reduced catch-up effects have been identified as key drivers of the slowdown. For modern China capital misallocation and diminishing convergence are also key factors, although other determinants such as structural change, R&D or FDI also receive attention. Literature on the "Japanification" of China is scarce but growing. There are recent studies on demand-side factors, but the supply-side papers rely on older data, and some of the key TFP determinants described above have not been analysed. This provides motivation for our supply-side analysis of Chinese TFP growth in the context of the "Japanification" threat.

3. Methodology & Data

3.1. Methodology

Given the many studies analysing the TFP slowdown in Japan and its determinants, this paper's empirical contribution focuses on China, as discussed in the previous section.

3.1.1. National TFP Growth & Index Construction

National TFP growth is calculated using the Solow residual method on an augmented Cobb-Douglas production function

$$Y = AK^\alpha(hL)^{1-\alpha} \quad (1)$$

Where Y is estimated as real GDP based on national accounts, A is TFP, K is capital services, a measure of the productive capacity of the capital stock, α is the capital share of income (we assume the labour share of income to be $1 - \alpha$), h is a human capital index, and L is effective labour input, calculated as total employment times the average annual hours per employee. Taking logs and differentiating, we can rearrange this formula into

$$\frac{\dot{A}}{A} = \frac{\dot{Y}}{Y} - \alpha \frac{\dot{K}}{K} - (1 - \alpha) \left(\frac{\dot{h}}{h} \right) - (1 - \alpha) \left(\frac{\dot{L}}{L} \right) \quad (2)$$

Hence, TFP growth $\frac{\dot{A}}{A}$ can be obtained as the residual unaccounted growth in GDP $\frac{\dot{Y}}{Y}$ when the growths in other inputs of production have been subtracted according to their weights. As mentioned in section 2.1, growth accounting is not a perfect framework for measuring TFP because it treats it as exogenous. However, this approach is necessary because we seek to find the determinants of TFP growth empirically rather than establish them *a priori*.

We also construct a TFP index that compares Japan and China's TFP levels to those of the US. The purpose of this exercise is to determine how close each country is to the technological frontier, using the US as a proxy for that frontier, given that it commonly has the highest TFP levels, and following the example of Penn World Table (Feenstra et al., 2015). This necessitates *level* data rather than *growth*, but the methodology is similar. First, we construct Törnqvist bilateral weights defined as the average of the labour and capital share of income between country i and the US:

$$s_L^T = \frac{s_L^i + s_L^{US}}{2} \quad (3)$$

$$s_K^T = 1 - s_L^T \quad (4)$$

Then we rearrange the production functions of both countries to find

$$TFP\ Index_i = \frac{\left(\frac{Y_i}{K_i^{s_K^T} (hL)_i^{s_L^T}} \right)}{\left(\frac{Y_{US}}{K_{US}^{s_K^T} (hL)_{US}^{s_L^T}} \right)} \quad (5)$$

3.1.2. Provincial TFP Growth Construction

The construction of TFP growth at the Chinese provincial level is conceptually similar to TFP growth at the national level, using the equation:

$$\frac{\dot{A}}{A} = \frac{\dot{Y}}{Y} - \alpha \frac{\dot{K}}{K} - (1 - \alpha) \frac{\dot{L}}{L} \quad (6)$$

In this case, we will be excluding human capital h from our factors of production, and thus the provincial measure of TFP growth will include growth in human capital. As shown by Bai and Zhang (2016), in studies that consider human capital as a factor determining TFP growth, it should not be treated simultaneously as an input factor. Since human capital will be a determinant in the main regression, we therefore exclude it.

Moreover, due to a lack of data on average hours worked per employee by province, our new measure of $\frac{\dot{L}}{L}$ is simply growth in employed persons. $\frac{\dot{Y}}{Y}$ is estimated as growth in Gross Regional Product (GRP), and $\frac{\dot{K}}{K}$ is estimated as growth in physical capital stock. Cross-province panel data on the capital income share α are difficult to obtain, so we use national-level time series data from the Penn World Table (Feenstra et al., 2015) and assume the capital income share is constant across provinces. These choices are consistent with other provincial studies on Chinese TFP growth (Zhou and Dahal, 2024; Tian and Yu, 2012).

For a robustness check, we also construct alternative TFP growth estimates using a capital share of income that varies by province but is constant across years, using provincial labour income share data from Chi and Qian (2013). Since they calculate a mean labour share of income over the 1997-2007 period only, we prefer the 1992-2022 national time series α for our main results.

3.1.3. Empirical Model

This paper uses the TFP growth estimates as the dependent variable of a panel regression to analyse its determinants. We include several specifications with and without province-level and year Fixed Effects (FE), as well as Two-Way Fixed Effects (TWFE), and with varying numbers of control variables depending on data availability (for example, data on growth in provincial R&D intensity is only available from 2007 onwards).

Following the example of Bai and Zhang (2016), we group explanatory variables according to the broad TFP determinants we seek to analyse: convergence to the frontier and capital misallocation. We focus on these determinants in particular because they are the most frequently cited explanations for Japan's collapse in TFP growth. Controls for other TFP determinants frequently found in global literature on TFP growth are also included.

3.1.3.1. Indicators of convergence to the technological frontier

The main indicator for this determinant group is the Distance To The Frontier Index (DTFI), calculated as deflated GRP per capita relative to deflated US GDP per capita at constant 2021 USD prices, as in Bai and Zhang (2016). DTFI ranges from 0 to 1, with values closer to 1 indicating proximity to the technological frontier. A potential threat to identification is reverse causality: while we hypothesise that a higher DTFI – meaning closer proximity to the frontier – reduces catch-up TFP growth, TFP growth itself raises GRP per capita and thus mechanically increases DTFI within the same period. This simultaneity would bias the DTFI coefficient toward zero, understating the convergence effect. To address this, we use DTFI lagged by 1 year, so that the frontier distance is predetermined relative to current TFP growth. Indicators that represent shares in total value added are not lagged, since we aim to capture the contemporaneous relationship between sectoral production and productivity, and we do not expect productivity outcomes to meaningfully shift slow-moving sectoral shares during the same year. Both of these choices are consistent with previous literature on Chinese TFP growth determinants (Bai and Zhang, 2016; Zhou and Dahal, 2024).

Other determinants expected to move in the same direction as GDP per capita and thus to capture convergence to the technological frontier include structural change measured as % of GRP in the tertiary sector, as the country transitions from a manufacturing to a services-focused economy; and ageing population, measured as share of people aged above 65 over total population¹, as the country completes its demographic transition.

3.1.3.2. Indicators of misallocation of capital

We use two indicators to measure capital misallocation. The first is a “zombie index”, inspired by Caballero et al. (2008). This variable uses firm-level data to measure the presence of “zombies” in Chinese provinces, meaning operationally unproductive firms that nonetheless consistently receive lending from banks. We classify “Zombies” as firms that report little or no difficulty accessing financing and also report negative revenue growth over the previous 3 years. These data are obtained from a 2024 World Bank survey of over 2,000 Chinese firms. The share of zombies in total enterprises constitutes the “zombie intensity” provincial flag. Since the survey data are time-invariant and classified by region, not province, we assign the same zombie intensity to all provinces in a given region. This implies the variable is collinear with province or year fixed effects and can only be identified in pooled OLS. Therefore, we note that the results for this indicator should be treated as indicative only and are vulnerable to bias.

The second indicator is the share of real estate in GRP, used as a proxy for capital allocation to real estate. As outlined above, the misallocation of capital and the presence of “zombies” in the Japanese episode were particularly pronounced in the real estate and construction sectors (Caballero et al., 2008; Ito and Sasaki, 2002; Fukao, 2000; Hosono and Sakuragawa, 2003). Similar concerns about inefficient real estate development and inflated prices have been raised in China (Zhao et al., 2017). Hence, we expect increased capital allocation in real estate to be relatively inefficient and thus to be associated with lower TFP growth. We note, however, that the real estate share of GRP is an imperfect proxy for misallocation: it may also reflect urbanisation, population inflows and genuine housing demand. A negative coefficient is therefore consistent with, but not uniquely attributable to, misallocation, and we treat it as suggestive. As a check, our robustness section replaces this measure with growth in real-estate firm liabilities, a more direct indicator of capital allocation to the sector.

3.1.3.3. Other controls

Global literature on TFP growth highlights R&D, human capital and trade openness as key determinants of productivity. R&D is included as growth in total R&D over GRP. Human capital is included as a 1-year-lagged growth in secondary education enrolment relative to the total population. Data on tertiary education would have been a better proxy, but it was not available. The lag aims to reflect that improvements in educational attainment take time to translate into higher workforce productivity, and we choose a 1-year lag because a 5-year or 10-year lag would seriously constrain our sample. Trade openness is measured as the sum of imports and exports over GRP.

Additionally, for the pooled OLS regression, we include a dummy variable that takes the value of 1 for the wealthy Eastern provinces (Beijing, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong).

Therefore, we expect TFP growth to be a function of distance to the frontier, capital misallocation, R&D intensity growth, human capital growth and trade openness as follows:

$$gTFP_{it} = \beta_0 + \beta_1 \text{Zombie}_i + \beta_2 \text{East}_i + \beta_3 \text{DTFI}_{it-1} + \beta_4 \text{Trade}_{it} + \beta_5 \text{Real Estate}_{it} + \beta_6 \text{Tertiary}_{it} + \beta_7 \text{LgHC}_{it-1} \\ + \beta_8 \text{AgeingPop}_{it} + \beta_9 \text{gR\&D}_{it} + \eta_i + \eta_t + \epsilon_{it}$$

Where *Zombie* is the zombie index, *East* is the dummy for wealthy provinces, *DTFI* is the distance to the frontier index, *Trade* is trade openness, *Real Estate* is the share of real estate in GRP, *Tertiary* is the share of tertiary sector in GRP, *LgHC* is the 1-year lag of growth in education enrolment as a share of population, *AgeingPop* is the share of the elderly in the total population, *gR&D* is the growth in R&D intensity, η_i are province fixed effects, η_t are year fixed effects, and ϵ_{it} is an error term.

This empirical model is not immune to endogeneity threats. Our TWFE estimators are demeaned within-province and within-period, and therefore, strict exogeneity is required for estimators to be consistent $E(\epsilon_{it}|X_{it}, \dots, X_{it}, \eta_i, \eta_t) = 0$, in addition to contemporaneous exogeneity (Wooldridge, 2010). This presents several endogeneity limitations: First, our model is vulnerable to time- and province-varying omitted confounding factors. We aim to address this by including various controls, but we may be missing other relevant ones. Second, our estimators may be correlated with TFP growth from other periods (dynamic feedback bias, violating strict exogeneity), or there may be reverse causality within periods (violating contemporaneous exogeneity, a weaker assumption). Some regressors are lagged to address reverse causality, but dynamic feedback bias is harder to tackle². Third, measurement error in regressors may bias our results: our identification of provincial zombie intensity by using regional averages necessarily introduces measurement error for each province, and our use of relative income levels and secondary education as proxies for technological advancement and human capital may be imprecise. Given these limitations, there is risk of endogeneity in our estimators, and our coefficients may not offer a perfect causal interpretation.

3.2. Data

3.2.1. National TFP Growth & Index Data

Panel data from 1965 to 2023 for China, Japan and the US for GDP, capital services, employment, average hours worked per employee, labour share of income and a human capital index were obtained from Penn World Table (Feenstra et al., 2015) and are summarised below:

Table 1
National TFP Growth & Index Data

Variable	Observations	Mean	Std	Min	Max
Constant Price Real GDP (2021 USD bn)	177	8,238.6	7,413.3	335.5	31,047.6
Current Price Real GDP at current PPP (2021 USD bn)	177	8,465.4	7,371.9	450.6	30,892.2
Constant Price Capital Services (2021=1)	177	0.438	0.342	0.005	1.145
Current Price Capital Services at Current PPPs (USA=1)	177	0.581	0.397	0.039	1.548
Employment (mill.)	177	267.2	264.8	52.1	774.4
Avg. Hours Worked	177	2,031.0	226.9	1646.4	2485.6
Labour Share of Income	177	0.589	0.028	0.508	0.649
Human Capital Index	177	2.922	0.689	1.346	3.830
Countries: China, Japan, United States			Years: 1965-2023		

We use two different metrics for GDP and capital services for our TFP growth and TFP index estimates. Current price metrics are calculated using different Purchasing Power Parities (PPPs) each year, so they are useful for comparing countries at a given period. We therefore use them to construct our index of Chinese and Japanese TFP relative to US TFP. Constant price metrics use PPP and level data for one year (2021), and extrapolate to other years using national accounts growth rates, so they are useful for analysing growth rates over time in a single country. We therefore use them to compute a time series of TFP growth in China.

3.2.2. Provincial TFP Growth Data

The following table summarises the 1992–2022 panel data necessary to construct provincial TFP estimates for China:

Table 2
Provincial TFP Growth Data

Variable	Observations	Mean	Std	Min	Max
Growth in GRP	775	0.100	0.036	-0.054	0.256
Growth in Physical Capital Stock	775	0.137	0.060	-0.022	0.850
Growth in Employment	694	0.006	0.030	-0.260	0.227
National Labour Share of Income Time Series	31	0.577	0.013	0.558	0.605
Avg. Provincial Labour Share of Income	25	0.493	0.061	0.310	0.610

Provinces: Anhui, Beijing, Chongqing, Fujian, Gansu, Guangdong, Guangxi, Hebei, Heilongjiang, Henan, Hubei, Hunan, Inner Mongolia, Jiangsu, Jiangxi, Jilin, Liaoning, Shaanxi, Shandong, Shanghai, Shanxi, Sichuan, Tianjin, Yunnan, Zhejiang

Years: 1992 2022

GRP growth is obtained from the China NBS website and is available from 1992 onwards, constituting the lower bound of our panel. Growth in Physical Capital Stock is obtained from the estimates of Wang and Ma (2024) up to 2022, constituting the upper bound. The time-series labour share of income at the national level is obtained from Penn World Table (Feenstra et al., 2015). The provincial labour share of income is an average for each province over the years 1997, 2000, 2004, and 2007, and is obtained from Chi and Qian (2013).

There are no reliable panel datasets on employment growth across all provinces, so data collection for this variable was not straightforward: figures had to be sourced from individual provincial statistical yearbooks. This paper has been able to retrieve statistical yearbooks for 25/31 provinces listed above by accessing and translating the relevant documents from provincial statistical office websites and purchasing yearbooks from third-party vendors where necessary. Our sample of 25 provinces accounts for around 95% of China's GDP. For some provinces, there is only partial data (e.g., only post-2013 data for Anhui or only 2009–2019 data for Shanghai), which is why there are only 694 observations, rather than 775.

3.2.3. Provincial TFP Growth Determinants Data

The following table summarises the panel data for the TFP determinants.

Table 3
Provincial TFP Growth Determinants Data

Variable	Obs.	Mean	Within Std	Between Std	Overall Std	Min	Max	Years
DTFI	673	0.096	0.062	0.058	0.079	0.011	0.451	1993–2022
Trade	673	0.280	0.115	0.321	0.318	0.025	1.634	1993–2022
Real Estate	673	0.056	0.018	0.015	0.022	0.004	0.133	1993–2022
Tertiary	673	0.446	0.067	0.083	0.102	0.235	0.844	1993–2022
LgHC	490	0.070	0.066	0.027	0.069	-0.053	0.305	2002–2022
Ageing Pop	490	0.147	0.034	0.021	0.040	0.083	0.273	2002–2022
gR&D	380	0.042	0.080	0.020	0.082	-0.253	0.497	2007–2022
RE gLiab	490	0.228	0.185	0.052	0.192	-0.169	1.862	2002–2022
RE gEmp	490	0.049	0.153	0.040	0.158	-0.455	0.812	2002–2022

Provinces: Anhui, Beijing, Chongqing, Fujian, Gansu, Guangdong, Guangxi, Hebei, Heilongjiang, Henan, Hubei, Hunan, Inner Mongolia, Jiangsu, Jiangxi, Jilin, Liaoning, Shaanxi, Shandong, Shanghai, Shanxi, Sichuan, Tianjin, Yunnan, Zhejiang

The variables *RE gLiab* and *RE gEmp* correspond to growth in total liabilities and growth in employment in real estate enterprises and will be used in the robustness check section.

The real GRP growth rate data necessary to construct a GRP deflator for a constant 2021 USD prices time series, the provincial GRP and GRP per capita data, import and export data, value added in the real estate and tertiary sectors, data on total secondary education enrolment, the ratio of persons aged above 65 over total population³ and the growth in liabilities and employment in real estate enterprises were obtained from the China NBS data website. Data for R&D intensity are from the 2022 and 2012 issues of the China Statistical Yearbook on Science and Technology, and were purchased from a third-party vendor. US real GDP per capita at constant 2021 USD prices was obtained from Penn World Table 11.0 (Feenstra et al., 2015).

The *Zombie* and *East* variables are time invariant and not fully heterogeneous across provinces, so they can only be used with pooled OLS. The *East* variable requires no data, and the *Zombie* data was obtained using data from the World Bank China 2024 Enterprise Survey. Using the criteria defining zombies outlined above, the distribution of such firms is as follows:

Table 4
Zombie Intensity by Region

Sampling Region	Zombie Flag		Total
	0	1	
North	284 82.8%	59 17.2%	343 100%
Northeastern	192 68.6%	88 31.4%	280 100%
East	436 77.9%	124 22.1%	560 100%
Central	362 79.6%	93 20.4%	455 100%
Southwest	230 87.1%	34 12.9%	264 100%
Northwest	251 87.5%	36 12.5%	287 100%
Total	1,755 80.2%	434 19.8%	2,189 100%

Upon request, the World Bank confirmed which provinces are included in each sampling region, but could not disclose the province of each individual firm⁴. Therefore, we assign a constant value for “zombie intensity” (e.g. 17.2% for North) for all the provinces in a given region. We note that some of the World Bank’s classifications are unusual (e.g. Guangdong as a central region), so although we match provinces to their correct World Bank classification for the purposes of our regression, we use a different classification where appropriate in Section 4.

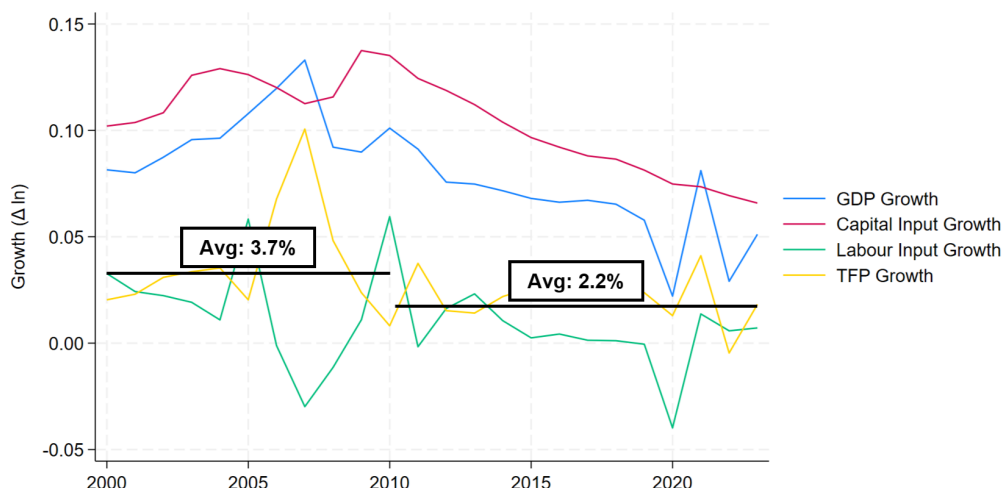
Our data suggest that around 20% of Chinese firms are classified as zombies, a result discussed in Section 5 and not far from estimates for 1990s Japan (Caballero et al., 2008). Interestingly, the Northeastern region ranks highest in zombie intensity, including Liaoning, Jilin and Heilongjiang. This could be explained by the fact that this region, known to be the old industrial heartland of China, has a higher state ownership and lower firm-level profitability than the national average (Geng and Weiss, 2007).

4. Main Results

4.1. National GDP Growth Decomposition in China, 2000-2023

The following chart decomposes the Chinese GDP growth into growth in capital input, labour input and TFP growth in 2000-2023:

Figure 2: GDP Growth Decomposition in China, 2000-2023 (Source: Author's calculation based on data from Penn World Table)

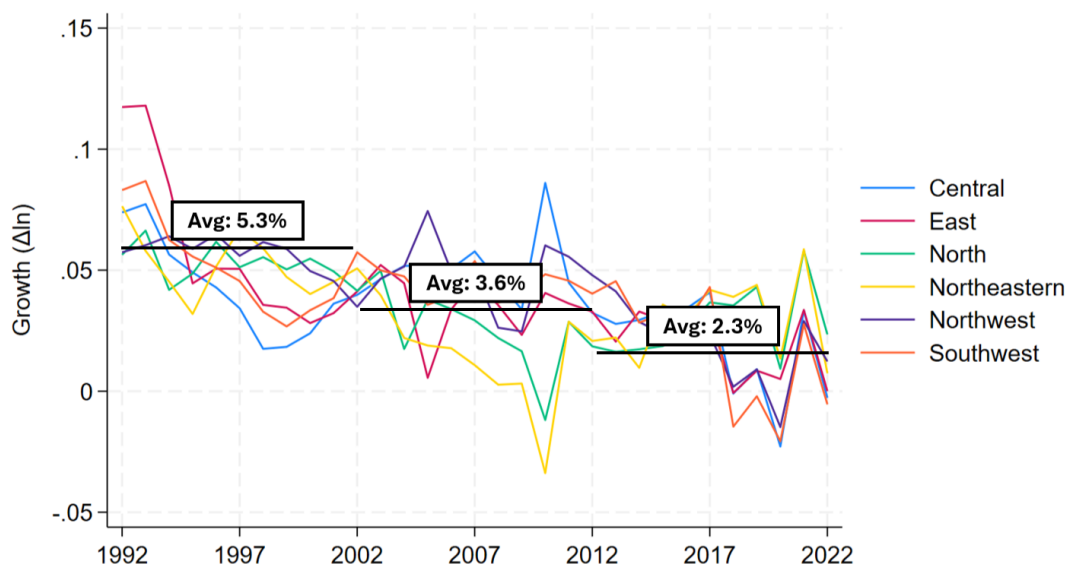


These data suggest that the fall in GDP growth from 10% on average before 2010 to 5.3% in 2023 was driven by a sustained slowdown in capital accumulation, which is expected for a maturing economy according to the Solow growth model, reduced growth of labour input (growth in employment and human capital attainment)⁵, and, notably, a fall in TFP growth from an average of 3.7% annually in 2000-2010 to 2.2% annually in 2010-2023.

4.2. Provincial TFP Growth 1992-2022

The results for the 30-year TFP growth estimates for 25 Chinese provinces, as well as 10-year national averages, are summarised by region below:

Figure 3: TFP Growth by Region in China, 1992-2022 (Source: Author's calculation)



Our updated provincial estimates up to 2022 are a new contribution to the literature and also display the downward trend seen in the national-level results, which is even more pronounced in 1992-2000. With a few exceptions, TFP growth has remained positive but close to 0 over the last 5 years⁶. The next section will attempt to explain the drivers of this measured TFP slowdown.

4.3. Determinants of TFP Growth

The table below summarises the results for our panel regression of TFP growth against various determinants. Eight specifications are included: (1) and (2) are pooled OLS; (3), (5) and (7) include province FE; and (4), (6), (8) include TWFE. Some controls are only available from 2002 or 2007 onwards, which is why there are multiple specifications for FE and TWFE covering different time periods.

Table 5
Panel Regression Results

	(1) 1993-2022	(2) 2002-2022	(3) 1993-2022	(4) 1993-2022	(5) 2002-2022	(6) 2002-2022	(7) 2007-2022	(8) 2007-2022
Zombie	-0.045* (0.025)	-0.057 (0.037)						
East Wealthy	0.009* (0.004)	0.003 (0.007)						
Lagged DTFI	-0.053* (0.031)	-0.010 (0.045)	-0.080* (0.043)	-0.073 (0.074)	-0.087 (0.081)	-0.085 (0.141)	-0.201** (0.086)	-0.471*** (0.148)
Trade	0.005 (0.006)	0.006 (0.006)	-0.023 (0.014)	-0.029* (0.015)	-0.027 (0.017)	-0.030 (0.021)	-0.057*** (0.018)	-0.088*** (0.023)
Real Estate	-0.524*** (0.107)	-0.404* (0.216)	-0.312* (0.165)	-0.274 (0.196)	-0.411 (0.251)	-0.437* (0.239)	-0.263 (0.280)	-0.412 (0.258)
Tertiary	0.027 (0.031)	0.018 (0.041)	-0.036 (0.059)	0.058 (0.073)	0.010 (0.064)	0.017 (0.076)	-0.050 (0.082)	-0.111 (0.092)
Lagged gHC		0.030 (0.020)			-0.000 (0.027)	0.012 (0.043)	-0.035 (0.070)	0.042 (0.075)
Ageing Pop		-0.042 (0.051)			-0.056 (0.074)	0.059 (0.109)	0.074 (0.079)	0.140 (0.121)
gR&D Intensity							-0.033 (0.025)	0.003 (0.020)
Observations	673	490	673	673	490	490	380	380
No. of provinces	25	25	25	25	25	25	25	25
Within R ²			0.194	0.329	0.122	0.245	0.125	0.306
Between R ²			0.032	0.044	0.014	0.025	0.000	0.001
Overall R ²	0.169	0.092	0.082	0.222	0.038	0.106	0.009	0.012
Province FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	No	No	No	Yes	No	Yes	No	Yes

Notes: Dependent variable: TFP growth. Clustered standard errors by province in parentheses. FE denote fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Our preferred specifications are (6) and (8), which include TWFE and the most controls for the periods 2002–2022 and 2007–2022, respectively. Given the identification limitations discussed in Section 3.1.3, we interpret these coefficients as conditional associations rather than causal effects. The coefficients of each of the indicators can be interpreted as follows:

4.3.1. Indicators of convergence to the technological frontier

The proxy for distance to the frontier (DTFI) is negative and significant in 4/8 specifications. Notably, in specifications (7) and (8), which cover 2007–2022, it turns strongly negative and significant, particularly in the TWFE regression. This interesting result holds even after dropping some controls or slightly modifying the time period (it is also strongly significant from 2006 and 2005). It suggests that China has indeed experienced reduced catch-up TFP growth due to technological convergence, but this process only began to take effect in the mid-2000s, by which time the income-per-capita gap with the US had already been considerably narrowed. A within-province-one-standard-deviation rise in lagged DTFI is associated with a 2.9pp fall in annual TFP growth in (8) versus 0.5pp in (6).

The other indicators of convergence (Tertiary and AgeingPop) turned out to be insignificant. The insignificance of AgeingPop should be read with a measurement caveat: our proxy captures only market-measured effects, but ageing also raises demand for informal elder care, which is enforced into civil and criminal code in China. Because this care is economically valuable but excluded from GDP, ageing may depress measured output and labour input without a true loss of productive activity, a channel our estimates do not capture.

4.3.2. Indicators of misallocation of capital

The Zombie indicator for capital misallocation at the firm level is negative in both specifications and significant in (1), although its coefficient is not very large. However, given that it is used without FE, this result should be considered an initial indication rather than strong evidence that capital misallocation is associated with lower TFP growth.

The coefficient for Real Estate is negative across all specifications. It is statistically significant in 4/8 specifications, including (6), the TWFE specification for 2002–2022 (a one-standard-deviation increase here implies a 0.8pp reduction in TFP growth). It is close to being significant in (4), (5) and (8). The fact that Real Estate is less significant in (8) than in the 2002–2022 specification suggests that the acuteness of real estate capital misallocation may have waned in recent years. Nevertheless, alternative estimates for TFP growth and alternative proxies for real estate capital allocation yield significantly negative estimates for specification (8) as well in the robustness check section.

Therefore, this evidence is consistent with capital misallocation being a relevant determinant of the TFP slowdown, alongside convergence effects.

4.3.3. Other controls and considerations

The controls for growth in R&D Intensity and for lagged human capital growth are insignificant. The dummy control for Eastern wealthy provinces in specification (1) is significant but small. For trade openness, the coefficient is negative and significant in specifications (4), (7) and (8), although it is small. One possible explanation for this surprising result is that, within provinces, increased trade volumes were driven by exports from labour-intensive, low-value-added sectors with little available productivity gains.

Another consideration to flag is that, despite Within R^2 being reasonably high, Between R^2 is low across all FE specifications and very low for specifications (7) and (8). The data section shows a balanced amount of between and within variability for each regressor (within and between Std.), and dropping regressors has little impact on Between R^2 in (7) and (8), so what is making Between R^2 so low in these specifications is likely the sample time period (2007–2022). Differences in TFP growth drivers across provinces may be persistent over this period and, therefore, are captured by the province FE rather than the regressors. This is consistent with the idea that FE and TWFE estimators are designed to capture within-cross-section (within-province) variation (Wooldridge, 2010), so we believe this limitation is not critical.

4.4. Robustness Checks

To test the robustness of the results above, we consider alternative estimates of TFP growth and proxies for real estate capital allocation. For conciseness, we focus only on our two preferred TWFE regressions, (6) and (8), and we show only selected coefficients. The full results for specifications (6) and (8) are included in Appendix Table A1.

We compute the alternative TFP growth estimates as described in Section 3.1.2. Growth in employment in real estate enterprises (*RE gEmp*) and growth in total liabilities in real estate enterprises (*RE gLiab*) are used as alternatives to the share of real estate in total value added (*Real Estate*).

Table 6
Robustness Check Results for Specifications (6) and (8)

	Baseline	Alternative TFP Growth Construction	Alternative Real Estate proxy	Alternative Real Estate proxy	Baseline	Alternative TFP Growth Construction	Alternative Real Estate proxy	Alternative Real Estate proxy
	(6)	(6)	(6)	(6)	(8)	(8)	(8)	(8)
	2002-2022	2002-2022	2002-2022	2002-2022	2007-2022	2007-2022	2007-2022	2007-2022
Lagged DTFI	-0.085 (0.141)	-0.066 (0.135)	-0.071 (0.142)	-0.085 (0.146)	-0.471*** (0.148)	-0.464*** (0.158)	-0.451*** (0.152)	-0.439*** (0.147)
Real Estate	-0.437* (0.239)	-0.493* (0.246)			-0.412 (0.258)	-0.552* (0.273)		
RE gEmp			-0.021* (0.010)				-0.018 (0.011)	
RE gLiab				-0.032*** (0.011)				-0.059*** (0.010)
Observations	490	490	490	490	380	380	380	380
No. of provinces	25	25	25	25	25	25	25	25
Within R ²	0.245	0.219	0.241	0.259	0.306	0.303	0.301	0.363
Between R ²	0.025	0.081	0.023	0.020	0.001	0.017	0.002	0.001
Overall R ²	0.106	0.132	0.123	0.122	0.012	0.028	0.012	0.019
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable: TFP growth. Clustered standard errors by province in parentheses. FE denote fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Our results for DTFI are unchanged across all specifications. The alternative TFP growth construction yields significantly negative estimates for *Real Estate* in both TWFE specifications. The alternative proxies are also significant in both specifications, except *RE gEmp* in (8). In particular, growth in the liabilities of real estate companies is a direct measure of capital allocation to real estate and is significantly negative in both specifications. Therefore, these results support our initial findings, consistent with convergence to the frontier after the mid-2000s and capital misallocation into real estate being associated with lower TFP growth.

As an additional check for the relatively small number of province clusters (25), we conduct wild-cluster-bootstrap-t inference at the province level for the robustness check specifications (6) and (8) above on our key variables. The significance pattern for lagged DTFI is unchanged: it remains insignificant in the 2002–2022 models and significant at the 1% level in the 2007–2022 models. The significance classifications of the real-estate measures are also unchanged, except for the liabilities-based proxy, which falls from 1% to 5% significance in both samples. Wild-cluster bootstrap p-values are included in Table A2. Overall, the small-cluster correction does not alter the paper's main conclusions.

5. Discussion

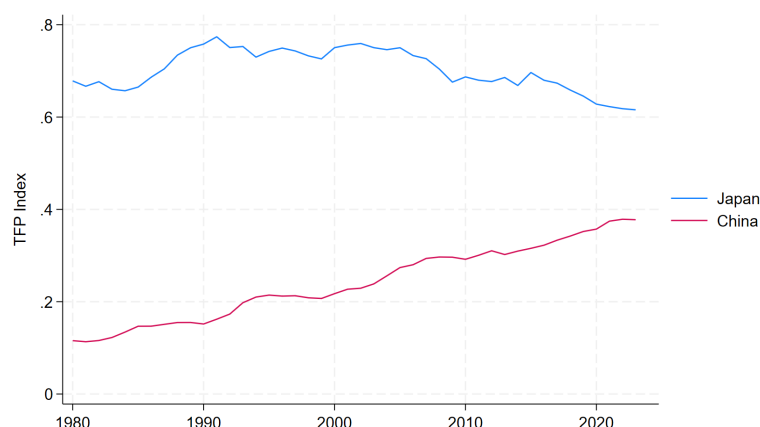
5.1. Comparison With 1980s-1990s Japan

The literature on Japan highlights two reasons for the slowdown in TFP growth in the 1980s-1990s: first, the exhaustion of 'catch-up' TFP growth as Japan converged in productivity to the US (Cameron, 2005; Comin, 2008), and second, capital misallocation at the firm level (Caballero et al., 2008; Fukao and Kwon, 2006; Nishimura et al., 2005), with real estate being a particularly problematic sector (Caballero et al., 2008; Ito and Sasaki, 2002; Fukao, 2000; Hosono and Sakuragawa, 2003). Our results suggest that, controlling for R&D intensity, growth in educational attainment, ageing population, trade openness, structural change and TWFE, these two factors are also associated with the observed decline in TFP growth in China. To assess whether China is likely to degenerate into a "Japanification" of TFP growth, we next compare the levels of these factors across the two countries descriptively.

5.1.1. Distance to the technological frontier

Using Penn World Table national data (Feenstra et al., 2015) for Japan, China, and the US, we can calculate a Törnqvist index of TFP levels for the two former countries relative to the latter, with the US serving as a proxy for the technological frontier, as explained in the methodology section. The following chart displays the calculated TFP indexes for Japan and China in 1980-2023.

Figure 4: TFP Levels Relative to the US (Source: Author's calculations based on data from Penn World Table)

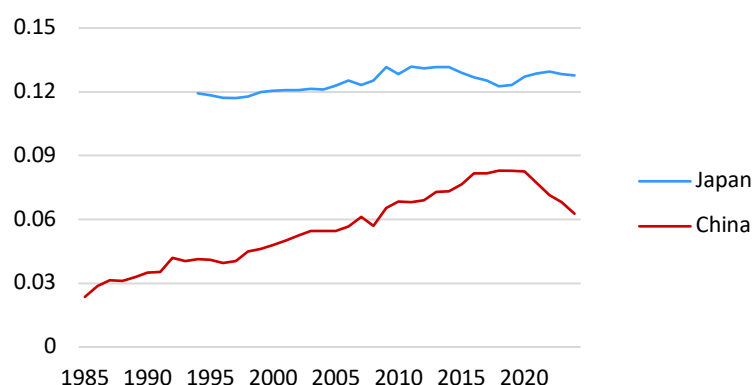


These results suggest that China still has lower TFP levels relative to the technological frontier than Japan did in the 1980s and 1990s. Japan hovered around 75% of American productivity levels in the lead-up to its crisis, but China has not yet reached 40% as of 2023. Therefore, despite the fact that the distance to the frontier indicator (DTFI) is strongly negative and significant, these results suggest China might still possess an “advantage from backwardness” (Gerschenkron, 1962), which might ease concerns of “Japanification” in the sense of closing the gap with the technological frontier.

5.1.2. Misallocation of Capital

Our classification of the 2,189 sample Chinese firms from the 2024 World Bank Enterprise Survey suggests that c.20% Chinese firms are zombies. This is close to the estimates of Caballero et al. (2008), which suggest zombie intensity in Japan hovered between 5-15% in 1981-1991, and then rose sharply to levels over 25% from 1993 onwards. Our data, therefore, suggest that zombie intensity is significant in China, but it has not yet reached the worst levels seen during the Japanese crisis. Regarding capital allocated to real estate, we have shown a negative correlation between the share of real estate in total output and TFP growth in China, but the levels of real estate dependency in 1980s-1990s Japan and modern China differ. The graph below uses international panel data from OECD for the share of real estate in total value added as an indicator of real estate dependency:

Figure 5: Share of Real Estate Activities in Total Value Added (Source: OECD, 2026)



Although there is no data prior to 1994 in Japan, it generally has a higher share of GDP in real estate activities, averaging around 13%, whilst China's share peaked at 8.3% in 2018. Given its smaller relative size, this suggests that unproductive capital invested in real estate is likely to be a smaller drag on overall TFP growth in China than in Japan. The decline in China's real estate share of total value added since 2018 is another promising signal, which may help explain why the Real Estate coefficient is insignificant in the reduced 2007–2022 TWFE sample.

Moreover, the capacity to meaningfully shape capital allocation into real estate is another important difference between the two countries. China's government and public-sector bodies wield significantly more influence over real-estate prices and investment than Japan did in the 1980s–1990s (Zhao et al., 2017). Indeed, Xi Jinping's leadership has been characterised by an emphasis on both party control (“The leadership of the Communist Party of China is the defining feature of socialism with Chinese characteristics”; Xinhua, 2021) and responsible growth (“Housing is for living and not for speculation”; Xinhua, 2021). In the real estate sector, this has led to a rise in the share of SOEs from 39% in 2019 to 59% in 2022 (Tian, 2023) and to policies such as the “Three Red Lines” to prevent capital misallocation, which are discussed further in the next section.

In conclusion, our empirical analysis shows that China is at risk of “Japanification” in productivity growth, given that TFP growth is associated with the same factors the literature links to Japan's TFP growth collapse. However, substantial differences in both distance to the frontier and extent of capital misallocation remain, so that there is hope China will avoid full “Japanification” in the short to medium term. Policies to address this challenge are discussed in the next section.

5.2. Policy Recommendations

This paper highlights two core problems for Chinese TFP growth: technological convergence and firm-level capital misallocation. There is naturally little to do about the first problem, so our main recommendation is that China should learn from Japan's 1990s crisis by minimising sustained capital misallocation in firms.

First, China should limit inefficient overinvestment in real estate. Strong efforts to restrict access to financing for overleveraged real estate firms have already been made through the August 2020 Three Red Lines programme. However, Zheng et al. (2024) found that this policy's financial constraints were substantially lower for SOEs, given their access to privileged financing from state-controlled banks. Given the rising share of SOEs in Chinese real estate (Tian, 2023), it is important to curb this preferential relationship between state financiers and real estate SOEs.

Second, local governments should reduce their reliance on the real estate sector. Since land is publicly owned in China, local governments have relied on selling land-use contracts through Local Government Financing Vehicles (LGFVs). LGFVs' share of average total budgets rose from 20% in 2012 to 30% in 2021 and is now an indispensable component of their financing (Huang, 2023). However, LGFV land sales are unproductive relative to private-sector real estate, underscoring the artificial budgetary purpose they serve (Jin et al., 2025). Alternative forms of local government financing, such as monetising public services or decentralising tax collection from the national government, are plausible options to diversify provincial budgets away from real estate.

Third, China's financial system should not roll over debt or provide subsidised credit to unprofitable firms to avoid recognising losses. In Japan, banks continued to extend financing to insolvent borrowers to avoid writing off existing capital, hoping they would eventually recover. This was the main reason behind the rise of zombie firms (Hoshi, 2006; Caballero et al., 2008). China's banks should therefore use the Japanese crisis as a cautionary example of why a short-term write-down on an unprofitable investment is often preferable to letting inefficiency persist in the economy.

6. Conclusion

China's growth slowdown shares many similarities with Japan's, but supply-side comparisons in the literature are scarce and rely on outdated data. The contribution of this paper is twofold: it has constructed updated provincial TFP growth estimates that show a downward trend in recent years, and it has found evidence consistent with convergence to the frontier and capital misallocation being key determinants of this slowdown. Both findings align with the literature on the Japanese TFP slowdown, indicating a significant risk of Japanification. However, China and Japan still differ in distance to the frontier, the extent of zombie firms in the economy, reliance on real estate, and government control over firms. Therefore, key policies that reduce favouritism towards SOEs, reduce government reliance on real estate revenues, and prevent capital from being consistently allocated to inefficient firms could help China avoid a “Lost Decades” scenario of near-zero TFP growth.

Avenues for future research include refining the calculation of TFP growth by incorporating natural resources and digital capital into the production function, since they are key inputs to production with increasing relevance. Moreover, updated data on physical capital stock could extend my analysis beyond 2022, enabling the study of determinants of TFP growth of critical contemporary relevance, such as investment in generative AI, digital infrastructure and champion industries such as

electric vehicles, renewable energy and batteries. Lastly, finding reliable data for an instrumental variable (IV) on real estate and DTFI could strengthen the causal interpretation of the results.

Notes

1. We note the share over 65 in total population is a noisy metric, but data for population over 80/85 were not available
2. We choose not to use a system GMM estimator to address dynamic feedback bias since our number of clusters (25) is not very large relative to our number of periods (28 in our 1993-2022 specifications), which would make the instruments unreliable (Roodman, 2009)
3. For this time series, there was no data available for census years 2010 and 2020 on the NBS website, so we extracted the data for those years from the China Statistical Yearbook of each year.
4. **North:** Beijing, Tianjin, Hebei, Shanxi, Inner Mongolia. **Northeastern:** Liaoning, Jilin, Heilongjiang. **East:** Shanghai, Jiangsu, Zhejiang, Anhui, Fujian, Jiangxi, Shandong. **Central:** Henan, Hubei, Hunan, Guangdong, Guangxi, Hainan. **Southwest:** Chongqing, Sichuan, Guizhou, Yunnan, Tibet. **Northwest:** Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang
5. The reason for the sharp fall in labour input growth in 2007 and 2008 was a measured drop in the average number of hours worked per employee.
6. The TFP growth volatility in 2010 results from unusual shifts in employment figures that year, which could be explained by measurement or benchmark revisions, since 2010 is a census year.

References

- Aghion, P. and Howitt, P. (1992). A Model of Growth Through Creative Destruction. *Econometrica*, 60(2), pp.323–351. doi:<https://doi.org/10.2307/2951599>.
- Bai, C.-E. and Zhang, Q. (2016). Is the People's Republic of China's current slowdown a cyclical downturn or a long-term trend? A productivity-based analysis. *Journal of the Asia Pacific Economy*, 22(1), pp.29–46. doi:<https://doi.org/10.1080/13547860.2016.1261438>.
- Banerjee, A.V. and Duflo, E. (2005). Chapter 7 Growth Theory through the Lens of Development Economics. *Handbook of Economic Growth*, pp.473–552. doi:[https://doi.org/10.1016/s1574-0684\(05\)01007-5](https://doi.org/10.1016/s1574-0684(05)01007-5).
- Barro, R.J. (1999). Notes on Growth Accounting. *Journal of Economic Growth*, 4(2), pp.119–137. doi:<https://doi.org/10.1023/a:1009828704275>.
- Brandt, L. et al. (2020). *China's productivity slowdown and future growth potential*. World Bank Policy Research Working Paper. doi:<https://doi.org/10.1596/1813-9450-9298>
- Caballero, R.J., Hoshi, T. and Kashyap, A.K. (2008). Zombie Lending and Depressed Restructuring in Japan. *American Economic Review*, 98(5), pp.1943–1977. doi:<https://doi.org/10.1257/aer.98.5.1943>.
- Cameron, G. (2005). The Sun Also Rises: Productivity Convergence Between Japan and the USA. *Journal of Economic Growth*, 10(4), pp.387–408. doi:<https://doi.org/10.1007/s10887-005-4735-6>
- Chi, W. and Qian, X. (2013) 'Regional disparity of labor's share in China: Evidence and explanation', *China Economic Review*, 27, pp. 277–293. doi: 10.1016/j.chieco.2012.10.004.
- Comin, D. (2008). *An Exploration of the Japanese Slowdown during the 1990s*. [online] Available at: <https://dcomin.host.dartmouth.edu/files/japan.pdf>.
- Eaton, J. and Kortum, S. (1999) *International technology diffusion: Theory and measurement*. *International Economic Review*, 40(3), pp. 537–570.
- Feenstra, R.C., Inklaar, R. and Timmer, M.P. (2015). The Next Generation of the Penn World Table. *American Economic Review*, 105(10), pp.3150–3182.
- Fukao, M. (2000) *Kin-yu Fukyo no Jissho Bunseki* [Empirical Analyses of Financial Recession]. Tokyo: Nihon Keizai Shinbun-sha.
- Fukao, K. and Kwon, H.-U. (2006). *Why did Japan's TFP growth slow down in the lost decade? An empirical analysis based on firm-level data of manufacturing firms*. *The Japanese Economic Review*, 57(2), pp.195–228. doi:<https://doi.org/10.1111/j.1468-5876.2006.00359.x>
- Fukao, K. and Yuan, T. (2016). China's Growth Slowdown: Lessons from Japan's Experience and the Expected Impact on Japan, the USA and Germany. *China & World Economy*, 24(5), pp.122–146. doi:<https://doi.org/10.1111/cwe.12177>.
- Geng, X. and Weiss, J. (2007) 'Development in North East People's Republic of China: An analysis of enterprise performance 1995–2002', *China Economic Review*, 18(2), pp. 170–189. doi: 10.1016/j.chieco.2006.06.005.
- Gerschenkron, Alexander. 1962. *Economic Backwardness in Historical Perspective*. Cambridge, MA: Harvard University Press.
- Hall, R.E. and Jones, C.I. (1999). *Why Do Some Countries Produce So Much More Output per Worker than Others?* National Bureau of Economic Research. Available at: <https://www.nber.org/papers/w6564>.
- Hayashi, F. and Prescott, E.C. (2002) 'The 1990s in Japan: A Lost Decade', *Review of Economic Dynamics*, 5(1), pp. 206–235. doi:10.1006/redy.2001.0149.
- Hoshi, T. (2006) 'Economics of the Living Dead', *The Japanese Economic Review*, 57, pp. 30–49. doi:10.1111/j.1468-5876.2006.00354.x.
- Hosono, K., and Sakuragawa, M. 2003, "Soft Budget Problems in the Japanese Credit Market," Nagoya City University Discussion Papers in Economics No.345
- Hsieh, C.-T. and Klenow, P.J. (2009). *Misallocation and manufacturing TFP in China and India*. *The Quarterly Journal of Economics*, 124(4), pp.1403–1448.
- Huang, T. (2023) *Why China's housing policies have failed*. Working Paper 23-5. Washington, DC: Peterson Institute for International Economics. Available at: JSTOR. doi:10.2307/resrep51234.
- Iida, T., Shoji, K. and Yoneyama, S. (2018) *What drives China's growth? Evidence from micro-level data*. Bank of Japan Working Paper Series, No. 18-E-19. Available at: https://www.boj.or.jp/en/research/wps_rev/wps_2018/data/wp18e19.pdf
- Ito, T. and Sasaki, Y.N. (2002) 'Impacts of the Basle Capital Standard on Japanese Banks' Behavior', *Journal of the Japanese and International Economies*, 16(3), pp. 372–397. doi:10.1006/jjie.2002.0509.
- Jin, Y., Ru, H., Yang, E. and Zou, K. (2025) *Redefining China's Real Estate Market: Land Sale, Local Government, and Policy Transformation*. SSRN. Available at: SSRN 5124537. doi:10.2139/ssrn.5124537.
- Kim, Y.E. and Loayza, N.V. (2019). Productivity Growth: Patterns and Determinants across the World. *Economía*, 42(84), pp.36–93. doi:<https://doi.org/10.18800/economia.201902.003>.
- Liu, M. (2025). The Japanification of China? A tale of two East Asian developmental states from the growth model perspective. *Competition & Change*. doi:<https://doi.org/10.1177/10245294251333197>.

- Lucas, R.E. (1988). On the Mechanics of Economic Development. *Journal of Monetary Economics*, 22(1), pp.3–42.
- Miller, S.M. and Upadhyay, M.P. (2000). The effects of openness, trade orientation, and human capital on total factor productivity. *Journal of Development Economics*, 63(2), pp.399–423. doi:[https://doi.org/10.1016/s0304-3878\(00\)00112-7](https://doi.org/10.1016/s0304-3878(00)00112-7).
- Murach, M. and Wagner, H. (2017). How severe will the growth slowdown in China caused by the structural change be? An evaluation based on experiences from Japan and South Korea. *Journal of Chinese Economic and Business Studies*, 15(3), pp.269–287. doi:<https://doi.org/10.1080/14765284.2017.1346930>.
- Nishimura, K.G., Nakajima, T. and Kiyota, K. (2005). *Does the natural selection mechanism still work in severe recessions?* *Journal of Economic Behavior & Organization*, 58(1), pp.53–78. <https://doi.org/10.1016/j.jebo.2004.03.008>
- OECD (2026) *Real Estate Activities as Percentage of Gross Value Added*. OECD Data Explorer. Available at: <https://data-explorer.oecd.org/> (Accessed: 16 April 2026).
- Romer, P.M. (1990). Endogenous Technological Change. *Journal of Political Economy*, 98(5), pp.S71–S102. doi:<https://doi.org/10.2307/2937632>.
- Rixtel, A.V. (2025). Whatever it takes? Economic Policymaking in China in the Context of a Possible Deflationary Spiral. *SSRN Electronic Journal*. doi:<https://doi.org/10.2139/ssrn.5574871>.
- Roodman, D. (2009) ‘A note on the theme of too many instruments’, *Oxford Bulletin of Economics and Statistics*, 71(1), pp. 135–158. doi: 10.1111/j.1468-0084.2008.00542.x.
- Solow, R.M. (1956). A Contribution to the Theory of Economic Growth. *The Quarterly Journal of Economics*, 70(1), pp.65–94. doi:<https://doi.org/10.2307/1884513>.
- Solow, R.M. (1957). Technical Change and the Aggregate Production Function. *The Review of Economics and Statistics*, 39(3), pp.312–320.
- Tian, X. (2023). China's Real Estate Development: A Deepening Gloom or A New Beginning. *BCP business & management*, 44, pp.366–375. doi:<https://doi.org/10.54691/bcpbm.v44i.4844>.
- Tian, X. and Yu, X. (2012). The Enigmas of TFP in China: A meta-analysis. *China Economic Review*, 23(2), pp.396–414. doi:<https://doi.org/10.1016/j.chieco.2012.02.007>.
- Wang, Q. and Ma, Z. (2024) ‘The measurement of China's provincial physical capital stock based on the improved method and indicators’, *PLOS ONE*, 19(8), e0307946. Available at: <https://doi.org/10.1371/journal.pone.0307946> (Accessed: 16 April 2026).
- Wooldridge, J. M. (2010). *Econometric Analysis of Cross Section and Panel Data* (2nd ed.). MIT Press, pp.265–269
- World Bank (2025) *China - World Bank Enterprise Survey 2024*. CHN_2024_WBES_v01_M. Washington, DC: World Bank Group. Available at: World Bank Microdata Library
- World Bank (2026) *GDP growth (annual %) - Japan, China*. World Development Indicators. Available at: <https://data.worldbank.org/indicator/NY.GDP.MKTP.KD.ZG?locations=JP-CN> (Accessed: 16 April 2026).
- Xinhua (2021) *Full text: Resolution of the CPC Central Committee on the Major Achievements and Historical Experience of the Party over the Past Century*. Available at: Gov.cn (Accessed: 2 April 2026).
- Yao, Y. (2016). Will China be Able to Avoid the Japan Syndrome? *China & World Economy*, 24(5), pp.98–121. doi:<https://doi.org/10.1111/cwe.12176>.
- Zhao, S.X.B., Zhan, H., Jiang, Y. and Pan, W. (2017). How big is China's real estate bubble and why hasn't it burst yet? *Land Use Policy*, 64, pp.153–162. doi:<https://doi.org/10.1016/j.landusepol.2017.02.024>.
- Zheng, X., Dong, Y. and Jiang, K. (2024) *Beyond the three red lines: Financing constraints and the performance of China's listed real estate companies*. SSRN, 6 August. doi:10.2139/ssrn.4916997.
- Zhou, Y. and Dahal, S. (2024). Has R&D contributed to productivity growth in China? The role of basic, applied and experimental R&D. *China Economic Review*, 88, p.102281. doi:<https://doi.org/10.1016/j.chieco.2024.102281>.

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Appendix

The following charts display our main TFP estimates by province. We follow the World Bank (2025) six-region geographic classification, with two slight modifications to align with commonly used regional schemes: Guangdong is treated as Eastern, not Central; and Guangxi is treated as Southwest, not Central.

Figure A1: TFP Growth in Central Provinces (Source: Author's Calculation)

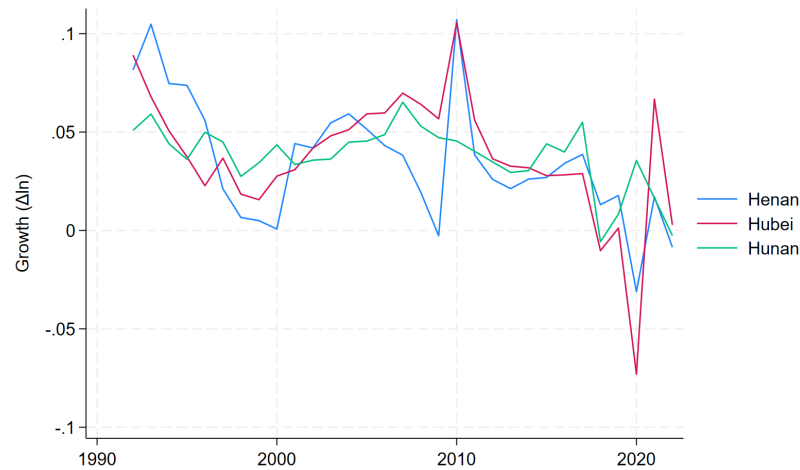


Figure A2: TFP Growth in Eastern Provinces (Source: Author's Calculation)

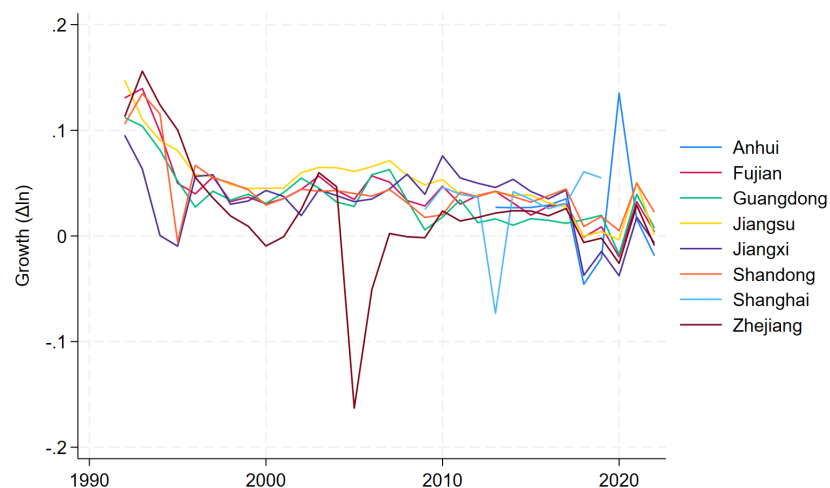


Figure A3: TFP Growth in Northern Provinces (Source: Author's Calculation)

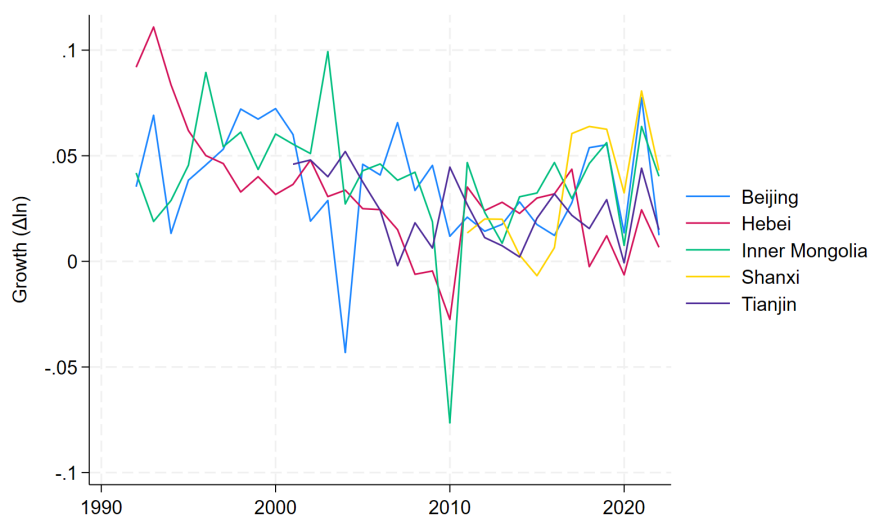


Figure A4: TFP Growth in Northeastern Provinces (Source: Author's Calculation)

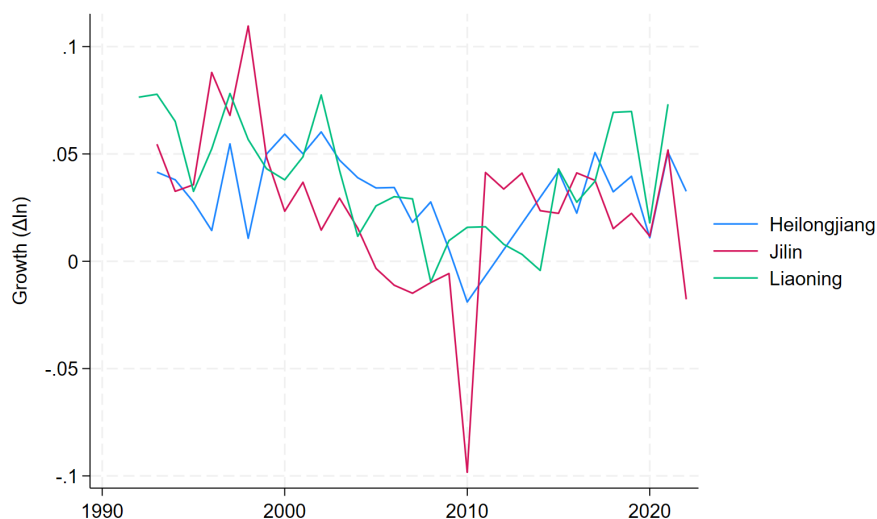


Figure A5: TFP Growth in Northwestern Provinces (Source: Author's Calculation)

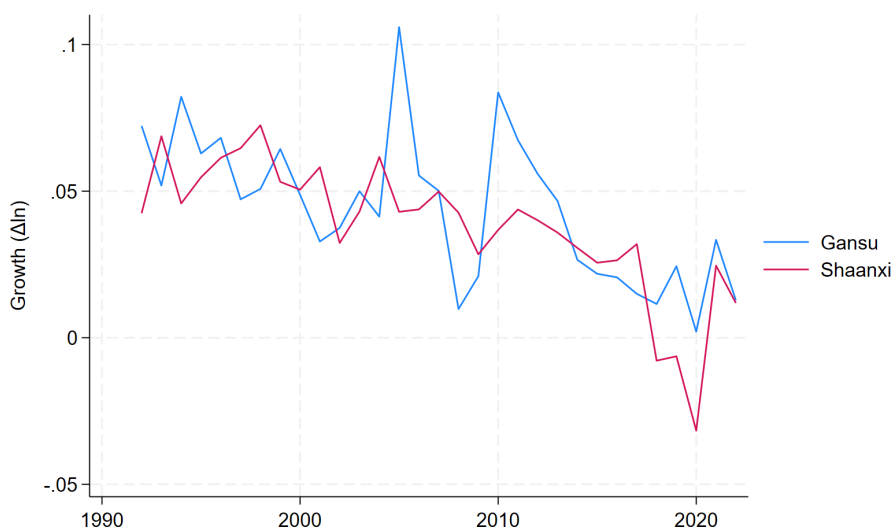


Figure A6: TFP Growth in Southwestern Provinces (Source: Author's Calculation)

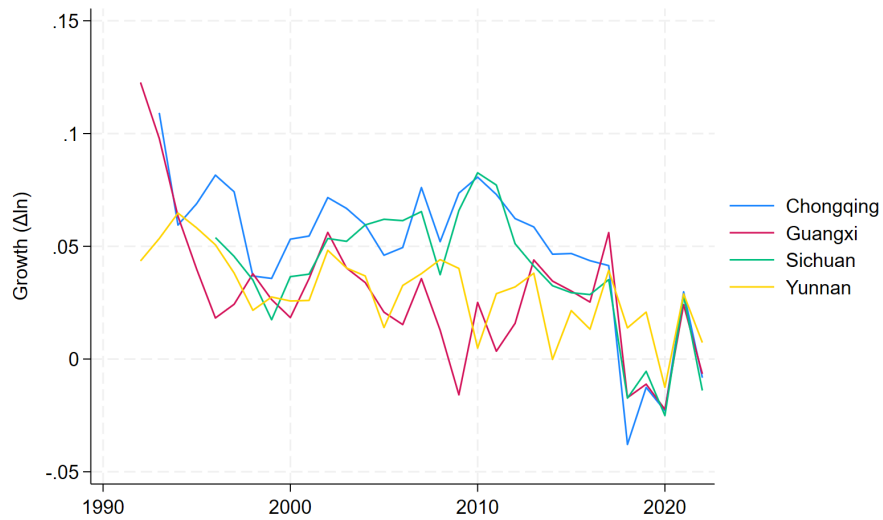


Table A1
Full Results for Robustness Check Regressions

	Baseline	Alternative TFP Growth Construction	Alternative Real Estate proxy	Alternative Real Estate proxy	Baseline	Alternative TFP Growth Construction	Alternative Real Estate proxy	Alternative Real Estate proxy
	(6)	(6)	(6)	(6)	(8)	(8)	(8)	(8)
	2002-2022	2002-2022	2002-2022	2002-2022	2007-2022	2007-2022	2007-2022	2007-2022
Lagged DTFI	-0.085 (0.141)	-0.066 (0.135)	-0.071 (0.142)	-0.085 (0.146)	-0.471*** (0.148)	-0.464*** (0.158)	-0.451*** (0.152)	-0.439*** (0.147)
Trade	-0.030 (0.021)	-0.030 (0.021)	-0.029 (0.022)	-0.034 (0.022)	-0.088*** (0.023)	-0.093*** (0.024)	-0.086*** (0.027)	-0.094*** (0.023)
Real Estate	-0.437* (0.239)	-0.493* (0.246)			-0.412 (0.258)	-0.552* (0.273)		
Tertiary	0.017 (0.076)	0.037 (0.082)	-0.038 (0.076)	-0.037 (0.075)	-0.111 (0.092)	-0.060 (0.099)	-0.178* (0.094)	-0.152* (0.075)
Lagged gHC	0.012 (0.044)	0.008 (0.043)	0.014 (0.048)	0.028 (0.045)	0.042 (0.075)	0.024 (0.078)	0.052 (0.075)	0.057 (0.070)
Ageing Pop	0.059 (0.109)	0.064 (0.120)	0.070 (0.105)	0.062 (0.101)	0.140 (0.121)	0.141 (0.131)	0.134 (0.127)	0.143 (0.121)
gR&D Intensity					0.003 (0.020)	0.006 (0.021)	-0.005 (0.023)	-0.004 (0.025)
RE gEmp			-0.021* (0.010)				-0.018 (0.011)	
RE gLiab				-0.032*** (0.011)				-0.059*** (0.010)
Observations	490	490	490	490	380	380	380	380
No. of provinces	25	25	25	25	25	25	25	25
Within R ²	0.245	0.219	0.241	0.259	0.306	0.303	0.301	0.363
Between R ²	0.025	0.081	0.023	0.020	0.001	0.017	0.002	0.001
Overall R ²	0.106	0.132	0.123	0.122	0.012	0.028	0.012	0.019
Province FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Dependent variable: TFP growth. Clustered standard errors by province in parentheses. FE denote fixed effects. * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A2
Small-Cluster Inference Robustness Check

Specification	Variable	Clustered p-value	Wild-cluster-bootstrap p-value
(6) Baseline	Lagged DTFI	0.554	0.6044
(6) Baseline	Real Estate	0.080	0.0953
(6) Alternative TFP	Lagged DTFI	0.628	0.6488
(6) Alternative TFP	Real Estate	0.056	0.0779
(6) RE gEmp	Lagged DTFI	0.623	0.6738
(6) RE gEmp	RE gEmp	0.059	0.0737
(6) RE gLiab	Lagged DTFI	0.566	0.6207
(6) RE gLiab	RE gLiab	0.009	0.0322
(8) Baseline	Lagged DTFI	0.004	0.0031
(8) Baseline	Real Estate	0.123	0.1282
(8) Alternative TFP	Lagged DTFI	0.007	0.0053
(8) Alternative TFP	Real Estate	0.054	0.0733
(8) RE gEmp	Lagged DTFI	0.007	0.0052
(8) RE gEmp	RE gEmp	0.120	0.1392
(8) RE gLiab	Lagged DTFI	0.006	0.0044
(8) RE gLiab	RE gLiab	<0.001	0.0154

Notes: Wild-cluster-bootstrap p-values are based on 9,999 replications with clustering and bootstrap resampling at the province level (25 clusters), using Rademacher weights