Equipment, Structures, and the Limits of Investment-Specific Technological Change*

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Abstract

The declining relative price of equipment has long been viewed as a primary driver of long-run growth through investment-specific technological change (ISTC). We document that this view overlooks a critical countervailing force: the rising relative price of structures. We establish four facts: (i) high-income countries face sharply rising structures price despite falling equipment prices; (ii) investment rates in equipment and structures respond negatively to their own prices; (iii) equipment prices predict income growth more strongly than structures price; and (iv) U.S. structures price increases are broad-based across categories. We develop a two-capital endogenous growth model where structures enter both production and R&D along with equipment. Calibrating to the U.S. economy, we find that the rising relative price of structures has reduced annual per-capita growth by about 0.50 percentage points since 1970. This "structural drag" operates through three channels: reduced capital deepening in production, higher R&D facility costs, and tighter economy-wide resources for innovation. Our findings help explain why rapid equipment ISTC has not translated into accelerating growth.

Keywords: Equipment, Structures, Investment-Specific Technological Change, Endogenous Growth
JEL Codes: O30, O40, E22

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1 Introduction

The decline in the relative price of equipment is one of the most robust features of the postwar U.S. economy. Since the seminal analysis of Greenwood et al. (1997), economists have viewed this trend as the signature of investment-specific technological change (ISTC) and a primary driver of long-run growth. By attributing productivity gains to the production of new, more efficient capital goods, this framework accounts for the major part of aggregate growth. Implicit in this consensus, however, is the assumption that the price of equipment is a sufficient statistic for the cost of capital, or that other investment goods share similar efficiency gains.

But treating all capital as the same misses an important difference in how production actually works. Capital formation involves two very different inputs: equipment to do the work, and structures to house that work. While the cost of equipment decreased sharply, the cost of building the physical structures has not dropped in the same way globally. This raises a key question: if machines get cheaper but the buildings needed to hold them get more expensive, does the cost of structures eventually drag down potential growth?

We argue that the divergence in capital prices creates a drag that significantly dampens the aggregate gains from investment-specific technological change. Utilizing data from the Penn World Table (PWT), the International Comparison Program (ICP), and the U.S. Bureau of Economic Analysis (BEA), we document four stylized facts.

First, we document a striking divergence in price trends based on income levels. While high-income countries benefit from rapidly falling equipment prices, they face sharply rising structures price relative to low-income countries. In the United States, the relative price of structures has risen particularly steeply, outpacing the general upward trend observed in other high-income nations. Second, we find that real investment rates in both sectors respond negatively to their own price levels. Third, we show that lower equipment prices are strongly associated with higher output per capita and total factor productivity (TFP), whereas structures price show a much weaker or insignificant association with these development indicators. Finally, focusing on the U.S., we observe that the post-1970 decline in equipment price was driven largely by information technology, whereas the post-1990 rise in structures price was broad-based across all categories, suggesting an economy-wide shift in the cost of producing structures.

To quantify the implications of this imbalance, we develop an endogenous growth model with two capital stocks. Unlike standard models where capital is aggregated or structures are assumed to be technologically neutral, our framework requires both equip-

ment and structures for final production and R&D. In other words, our model introduces two types of capital (equipment and structures) in the "lab equipment" formulation of endogenous growth Rivera-Batiz and Romer (1991) and quantify the consequences of the ISTC both in equipment and structures. We characterize the balanced growth path and derive "growth multipliers" that weight the contribution of each capital type.

We find that the rising relative price of structures acts as a drag on growth, both by reducing capital deepening and by restricting the resource available for innovation. The structural drag operates through two distinct channels. First, the direct input channel arises because structures (such as laboratories and offices) are physical inputs in knowledge production. Slower efficiency growth in this sector directly raises the cost of R&D facilities. Second, the indirect resource channel operates through the final-goods constraint. Sluggish productivity in the structures sector dampens aggregate output growth and capital accumulation, thereby tightening the resources available for innovation.

We calibrate the model to the U.S. economy and compare it to a standard one-capital model which assumes all capital benefits from the same rapid efficiency growth as equipment. We find that the one-capital model significantly overestimates U.S. growth, predicting a 2020 GDP per capita nearly double the observed data. This is because it ignores the productivity bottleneck created by the structures sector. By contrast, our two-capital model closely tracks observed U.S. growth trajectories.

Quantitatively, our model since 1970 yields an average per-capita output growth of 1.46 percentage points annually. Of this, ISTC contributes 0.82 percentage points in net terms, reflecting a substantial equipment boost of 1.32 percentage points partially offset by a structural drag of 0.50 percentage points, while the remaining 0.64 percentage points arise from the population component. This "structural drag" operates through three channels: reduced capital deepening in production (0.38 percentage points), higher R&D facility costs (0.06 percentage points), and tighter economy-wide resources for innovation (0.06 percentage points).

A natural concern is that the secular rise in the relative price of structures may partly reflect deflator mismeasurement rather than a true decline in construction productivity. We address this concern using estimates from Garcia and Molloy (2025), who quantify the potential bias in construction price indices. Even under their most generous upper-bound estimate of 0.8 percentage points per year, measurement error can attenuate but cannot eliminate the quantitative importance of structural drag.

We perform a counterfactual analysis to assess the global implications of these trends. We feed the historical relative price series of representative high-income (HIC) and low-

income economies (LIC) into our calibrated model. We find that the counterfactual U.S. economy with the representative high-income economies' price series generates higher ISTC-induced growth than the United States. The gap driven almost entirely by the severe "structural drag" in the U.S. sector. Of the 0.35 percentage points gap in ISTC-induced GDP per capita growth rate between the HIC counterfactual (1.17 percentage points) and the U.S. baseline (0.82 percentage points), 82.9% (0.29 percentage points) is explained by the structures margin.[1] Conversely, relative to the counterfactual U.S. economy with the representative low-income economies' price series, the United States still achieves higher growth. While low-income countries benefit from the absence of a structural drag, this stability is insufficient to outweigh the substantial "equipment boost" enjoyed by the U.S.. Relative to the LIC counterfactual, the U.S. 0.10 percentage points advantage in GDP per capita growth rate reflects a 0.56 percentage points equipment advantage that is offset by a 0.46 percentage points larger structural drag.

Finally, we extend the model to allow for CES aggregation of equipment and structures in both production and R&D. The magnitude of the structural drag depends on the elasticity of substitution between the two capital types. If equipment and structures are complements, firms cannot easily substitute away from structures when their relative cost rises, amplifying the drag. If they are substitutes, firms can shift toward cheaper equipment, attenuating the drag.[2] Our Cobb-Douglas baseline which imposes unit elasticity represents a middle ground between these cases.

Our work connects to four areas of research. First, we build upon the foundational literature on investment-specific technological change (ISTC). Greenwood et al. (1997) established the relative price of equipment as a sufficient statistic for technological progress in the investment sector, attributing the bulk of postwar growth to the decline in this price. We depart from this framework by explicitly modeling the heterogeneity between equipment and structures. While we confirm their finding regarding the efficiency gains in equipment, we document that the rising relative price of structures constitutes a countervailing force.[3]

Second, our framework builds on the "lab-equipment" formulation of endogenous growth (Rivera-Batiz and Romer, 1991), in which capital goods are direct inputs into

[1] Because the population component is held fixed across scenarios, this gap also equals the difference in total per-capita growth rates (1.81 versus 1.46 percentage points).

[2] This resembles Baumol's cost disease (Baumol, 1967), where the extent of aggregate productivity slowdown depends on how easily the economy can substitute away from sectors with low productivity growth toward sectors with high productivity growth.

[3] The investment-specific technological change (ISTC) has also been used as an explanation for a wide range of macro trends, including the increasing skill premium (Krusell et al., 2000) and the falling labor share (Karabarbounis and Neiman, 2014).

R&D. In this class of models, ISTC unambiguously lowers the user cost of research capital, so the collapsing price of equipment should have fueled an explosion in idea production. We demonstrate why this has not occurred: the rising relative price of structures constitutes a countervailing force that raises R&D facility costs and tightens the resources available for innovation.[4]

Third, we contribute to the literature on relative prices and development accounting. Regarding relative prices, Jones (1994) documents a negative relationship between the relative price of capital and the rate of economic growth. We confirm this relationship using extended data and build a model that replicates it. Regarding development accounting, Hsieh and Klenow (2007) argue that low real investment rates in poor countries stem from the high relative price of investment goods. We refine this view by decomposing the investment bundle. We document that the dynamics of capital prices differ systematically by development level. Low-income countries have experienced a slower decline in equipment prices but also a slower increase in structures price compared to advanced economies. This implies a dual effect on global inequality. While the equipment channel favors divergence as rich nations benefit more from falling technology costs, the structure channel acts as a leveling force as economies at the technological frontier are disproportionately penalized.

Finally, we provide a macroeconomic transmission mechanism for recent micro-founded evidence on construction sector productivity. Goolsbee and Syverson (2023) document a secular decline in physical value-added per worker in the U.S. structures industry and call it "strange and awful path". We show that the decline of structures productivity is a binding constraint on the aggregate economy, effectively bottling up the potential gains from rapid decline in equipment prices.

2 Data and Stylized Facts

2.1 Data

Our primary panel dataset for cross-country analysis is constructed by merging two sources: the International Comparison Program (ICP) and the Penn World Table (PWT). We work at the country-year level and focus on the 1950–2019 period, which provides the broadest coverage of the disaggregated investment price series required for our analysis. For the

[4]Our approach is also related to Foerster et al. (2022), who quantify the role of particular sectors in trend GDP growth. While they employ a model with capital accumulation and network structure, we address this question within an endogenous growth framework.

analysis of the United States, we use the Fixed Assets Account tables from the Bureau of Economic Analysis (BEA). The definition of capital and the coverage of each dataset used in our analysis are discussed in Appendix A.

The core explanatory variables are the prices of investment goods by asset type. We obtain these from the World Bank's ICP, which reports Purchasing Power Parities (PPPs) for detailed expenditure categories. Rather than relying on aggregate investment price indices, we extract PPP series for two distinct capital categories: equipment[5] and structures.[6] This disaggregation is central to our analysis because it allows us to trace heterogeneous movements in relative prices across capital types and to link them to differential ISTC. In the empirical simulations, we proxy γ_E and γ_S with the long-run log growth rates of the corresponding ICP relative-price series.

Measures of aggregate economic performance and productivity are taken from PWT version 11.0 (Feenstra et al., 2015). We use output-side real GDP at current PPPs (`cgdpo`) as our main measure of aggregate output and the TFP series (`ctfp`) to characterize productive efficiency. To account for cross-country differences in labor quality, we include the human capital index (`hc`). We complement this measure with the PWT Labor Detail file, which provides more granular information on educational attainment. In particular, we use average years of schooling (`yr_sch`) primarily from Barro and Lee (2013). Finally, we use total population (`pop`) to control for scale.

2.2 Stylized Facts

Fact 1: High-income countries benefit from falling equipment prices but face sharply rising structures price relative to low-income countries.

We begin by examining trends in the relative prices of equipment and structures, utilizing data from the PWT. All price series are deflated by the GDP price index and normalized to 1 in 1970. We divide countries into three groups based on their 1970 GDP per capita: the top and bottom terciles are defined as the High Income Group and Low Income Group, respectively.

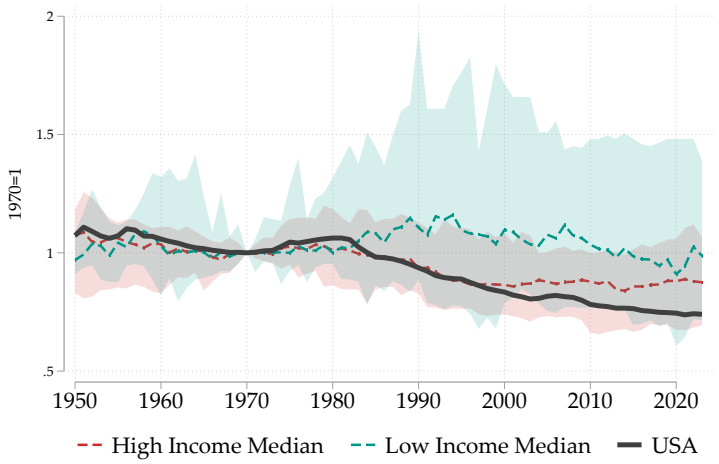
As shown in Figure 1, the relative price of aggregate investment declines after 1970 for the United States (solid black line) and for both income groups (dashed medians). The low-income median (green dashed line) is above the high-income median (red dashed

[5]We use the term 'equipment' consistently throughout. In the underlying data, related categories appear under varying labels (e.g., 'Machine and Equipment', 'equipment'); we harmonize these into 'equipment'.

[6]We mainly focus on equipment and structures, which together account for about 80% of total investment and over 90% of capital stock. As shown in Appendix B.1.1, their investment shares are stable over time and across regions.

line) for much of the post-1980 period, indicating a modest but visible divergence in central tendencies. In addition, the low-income group displays substantially greater cross-sectional dispersion, as reflected in the wider shaded band.

Figure 1: **Relative Investment Price Index Trend (1950-2020)**



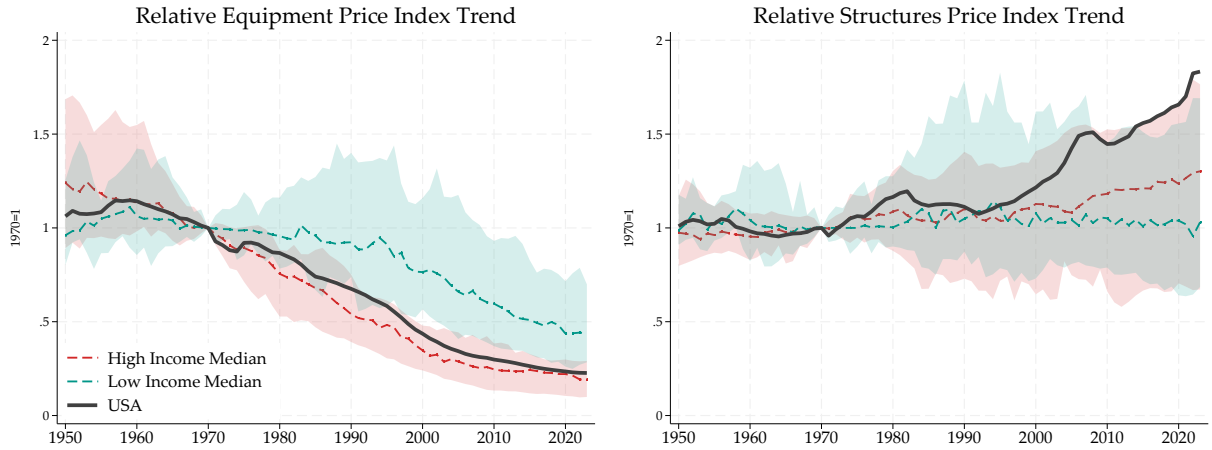
Notes: The relative price is calculated by dividing the investment price index by the GDP price index, normalized to 1 in 1970. High and low income groups are defined based on the top and bottom terciles of real GDP per capita in 1970. A total of 120 countries with reported prices in 1970 are included in the analysis. The low-income group (indicated in green) and the high-income group (indicated in red) represent the bottom and top terciles, respectively. Shaded areas represent the 15th to 85th percentile range. Dashed lines indicate the median for each group, and the solid black line denotes the United States. *Sources:* Penn World Table 11.0; PWT Capital Detail; and authors' calculations.

However, disaggregating investment into equipment and structures reveals striking differences.[7] The left panel of Figure 2 plots the evolution of equipment prices. The U.S. experienced the most rapid decline in equipment prices, even relative to other high-income economies. Notably, in contrast to the aggregate investment price, the median equipment price for the High Income Group falls significantly faster than that of the Low Income Group, which aligns with Lian et al. (2020).

The right panel of Figure 2 shows the evolution of relative prices for structures. Here, we observe a trend distinct from that of equipment. In this category, the United States exhibits a particularly steep increase, outpacing the general upward trend observed across the High Income Group. In sharp contrast, the Low Income Group displays a modest downward trend over the same period. Trends for the remaining asset categories (transport equipment and other assets) are reported in Appendix B.1.2. Finally, we obtain similar patterns when using capital-stock-based price indices for both sectors, as reported in Appendix B.1.3.

[7]PWT Capital Detail reports four different types of capital: Structures, equipment and Equipment, Transport Equipment, and Other. The other two capital trends and detailed capital measures are discussed in Appendix A.

Figure 2: **Relative Investment Price Index Trend by Sector (1950-2020)**



Notes: The relative price for each sector is calculated by dividing each sector's investment price index by the GDP price index, normalized to 1 in 1970. High and low income groups are defined based on the top and bottom terciles of real GDP per capita in 1970. A total of 120 countries with reported prices in 1970 are included in the analysis. The low-income group (indicated in green) and the high-income group (indicated in red) represent the bottom and top terciles, respectively. Shaded areas represent the 15th to 85th percentile range. Dashed lines indicate the median for each group, and the solid black line denotes the United States as a benchmark. Dashed lines indicate the median for each group, and the solid black line denotes the United States. *Sources:* Penn World Table 11.0; PWT Capital Detail; and authors' calculations.

In addition to the PWT, we also examine price trends using the ICP and confirm that the patterns we document in the PWT are also present in the ICP data. Following Hsieh and Klenow (2007), we normalize U.S. GDP per capita (measured in PPP terms) to one in each ICP survey year, and we likewise normalize each country's relative equipment price and relative structures price by the corresponding U.S. values to enable cross-country comparisons. Examining changes from 1996 to 2021, we find that countries' equipment prices relative to the United States increase on average, whereas relative structures price decline steadily. Over the same period, the correlation between relative equipment prices and GDP per capita decreases from 0.02 to -0.08, while the correlation between relative structures price and GDP per capita increases from 0.26 to 0.66. Appendix B.1.4 reports the corresponding plots as well as the estimated coefficient changes in the cross-sectional regressions across survey years.

Fact 2: Real investment rates in both sectors respond negatively to their relative prices.

To investigate the distinct roles of equipment and structures in economic development, we exploit disaggregated price and expenditure data from the ICP spanning the period from 1996 to 2021. The ICP data allows us to identify the specific price levels and investment volumes for each asset sector across countries. For cross-country comparability, we measure the price level of each asset type by dividing its Purchasing Power Parity

(PPP) based price by the exchange rate (relative to USD). In addition, we calculate the investment rate using the volume of investment in each sector and GDP measured in real PPP terms.

We explicitly employ the ICP data to capture the cross-country dispersion in absolute price levels across sectors, as these level differences are essential for identifying the distinct impact of asset-specific costs on investment rates in contrast to previous studies that rely on time-series price indices.[8] This is crucial because it preserves the cross-sectional variation in absolute price levels, allowing us to estimate the sensitivity of investment to the actual cost of capital assets rather than mere relative changes.

To identify the impact of asset-specific price levels on investment rates, we estimate a pooled regression model with country-year fixed effects as follows:

$$\ln\left(\frac{I_{it}^k}{Y_{it}}\right) = \beta_{\text{Equip}}^k \ln(P_{it}^{\text{Equip}}) + \beta_{\text{Str}}^k \ln(P_{it}^{\text{Str}}) + \mathbf{X}_{it}'\Gamma^k + \alpha_i^k + \delta_t^k + \epsilon_{it}^k, \quad k \in \{\text{Equip}, \text{Str}\} \tag{1}$$

where I_{it}^k/Y_{it} denotes the investment rate for asset type $k \in \{\text{Equip}, \text{Str}\}$. That is, the investment rate is defined as the ratio of the PPP-adjusted real investment volume in sector k to the PPP-adjusted real GDP. The key explanatory variables, $\ln(P_{it}^{\text{Equip}})$ and $\ln(P_{it}^{\text{Str}})$, denote the log price levels of equipment and structures in PPP, respectively, and normalized by the exchange rate. The vector $\mathbf{X}_{it}$ includes country-specific controls such as human capital and population structure.[9] α_i^k and δ_t^k represent country and year fixed effects, respectively.

The coefficients β_{Equip}^k and β_{Str}^k are the parameters of interest, capturing the price elasticities of investment rate of sector k. Specifically, the own-price coefficient measures ($\beta_{\text{Equip}}^{\text{Equip}}$ and $\beta_{\text{Str}}^{\text{Str}}$) the direct impact of capital costs on accumulation within the same sector; a negative sign implies that higher costs hinder investment. Meanwhile, the cross-price coefficients ($\beta_{\text{Equip}}^{\text{Str}}$ and $\beta_{\text{Str}}^{\text{Equip}}$) shed light on the inter-sectoral relationship. For instance, a negative cross-price elasticity would suggest that equipment and structures are complements in the production function, whereas a positive sign would imply substitutability.

[8] For instance, Lian et al. (2020) utilize the PWT Capital Detail dataset, which we utilize for Fact 1. However, the price variables in the PWT are normalized to 1 in a base year, which eliminates cross-sectional price level dispersion in that year. While this allows for the estimation of investment elasticity with respect to within-country price *trends*, it fails to capture the impact of absolute price *levels* across countries at a given point in time.

[9] Since the PWT human capital index is constructed in part from schooling data and relies on interpolation, the two measures may be mechanically correlated. Accordingly, we interpret their coefficients only as nuisance controls and verify in robustness checks that our key price elasticities are essentially unchanged when controlling for either schooling or the human-capital index.

We include a vector of controls $\mathbf{X}_{it}$: the human capital index and years of schooling to ensure that estimated price effects do not confound the impact of labor quality improvements; the logarithm of population to control for scale effects; and the 5-year lagged level of GDP per worker ($\ln y_{it-5}$) to account for conditional convergence dynamics. Finally, we include country fixed effects (α_i) to absorb time-invariant country-specific factors, such as geography and institutional heritage, and year fixed effects (δ_t) to control for global common shocks. Standard errors are clustered at the country level.

Table 1 presents the regression results for equation (1). The estimates highlight two distinct channels through which prices drive investment allocation.

Table 1: **The Effect of Capital Prices on Sectoral Investment Rates**

	Equipment Investment Rate (1)	Structures Investment Rate (2)
Relative prices		
Log Equipment Price	-0.469***	0.369**
	(0.128)	(0.152)
Log Structures Price	0.255***	-0.632***
	(0.086)	(0.066)
Controls		
Years of Schooling	0.737**	0.808**
	(0.336)	(0.353)
Human Capital Index	-3.248**	-4.258***
	(1.641)	(1.622)
Log Population	-0.560*	0.723***
	(0.323)	(0.262)
Lagged Log GDP per Worker	-0.088	-0.182
	(0.139)	(0.150)
Constant	0.364	-0.668
	(1.816)	(1.605)
Observations	629	629
R^2	0.708	0.682
Country FE	✓	✓
Year FE	✓	✓

Notes: Standard errors are reported in parentheses and are clustered at the country level. All specifications include country and year fixed effects. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

First, we find evidence of negative own-price elasticities in both sectors. As shown in column (1), a 1% increase in the relative price of equipment leads to a 0.47% decrease in the equipment investment rate. Similarly, column (2) indicates that a 1% increase in the price of structures reduces the structures investment rate by approximately 0.63%.

These results confirm that higher capital costs directly dampen accumulation within the respective sector. This result is consistent with Restuccia and Urrutia (2001), who find that the relative price of investment is negatively correlated with investment rates in a cross section of countries using data on 125 countries over 1960–1985.

Second, the cross-price elasticities reveal a significant substitution pattern between asset classes. The coefficient of the structures price on equipment investment is positive and significant (0.26), and likewise, the coefficient of the equipment price on structures investment is positive (0.37). This positive relationship implies that equipment and structures function as substitutes in the aggregate production function. Consequently, when the cost of one capital type rises, economies tend to optimize their input mix by reallocating resources toward the relatively cheaper capital type, rather than reducing aggregate investment uniformly.

Fact 3: Lower equipment prices are strongly associated with higher output per capita, whereas structures price show a much weaker association.

Having established the relationship between capital prices and sectoral investment rates, we next assess whether prices are transmitted directly to income levels. To this end, we estimate equation (1) after replacing the dependent variable with GDP per capita from the PWT. We then extend the baseline specification to a set of dynamic regressions that evaluate predictive content at different horizons. Specifically, we test whether current capital prices (P_{it}) predict contemporaneous and future income, and we additionally verify that they do not predict pre-determined past income. The latter serves as a placebo test for reverse causality and spurious correlation. We estimate the following specification for horizons $h \in \{-5, 0, 5\}$:

$$\ln(y_{i,t+h}) = \beta^h_{\text{Equip}} \ln(P^{\text{Equip}}_{it}) + \beta^h_{\text{Str}} \ln(P^{\text{Str}}_{it}) + \mathbf{X}'_{it}\Gamma^h + \lambda^h \ln(y_{i,t-\tau}) + \alpha^h_i + \delta^h_t + \epsilon^h_{it} \tag{2}$$

where τ denotes the lag length for the lagged GDP per capita. As a baseline, we estimate the effect of the current price measure on output at each horizon h (including the contemporaneous case $h = 0$), and we check robustness to using different lag lengths for the initial-income control, $\tau \in \{6, 10\}$.

Table 2 presents the estimated elasticities of GDP per worker with respect to capital prices across different time horizons. The results reveal two critical patterns. First, the timing of the correlation supports a interpretation running from equipment prices to economic development. As shown in Columns (1) through (3), the magnitude of the coefficient on equipment prices is heavily dependent on the time horizon. The current

Table 2: **The Effect of Capital Prices on GDP per Capita**

	Control: Lagged GDP ($t-6$)			Control: Lagged GDP ($t-10$)		
	$\ln(y_{i,t-5})$	$\ln(y_{i,t})$	$\ln(y_{i,t+5})$	$\ln(y_{i,t-5})$	$\ln(y_{i,t})$	$\ln(y_{i,t+5})$
	(1)	(2)	(3)	(4)	(5)	(6)
Relative prices						
Log Equipment Price	-0.045*	-0.279***	-0.235**	-0.179**	-0.318***	-0.223*
	(0.023)	(0.097)	(0.113)	(0.077)	(0.114)	(0.117)
Log Structures Price	-0.008	-0.064	0.019	-0.010	-0.104*	-0.031
	(0.014)	(0.048)	(0.062)	(0.036)	(0.055)	(0.060)
Controls						
Years of Schooling	0.064	0.310*	0.498**	0.404**	0.370*	0.405
	(0.051)	(0.165)	(0.247)	(0.159)	(0.207)	(0.262)
Human Capital Index	-0.347	-1.448*	-2.326*	-1.816**	-1.613*	-1.871
	(0.237)	(0.773)	(1.231)	(0.725)	(0.968)	(1.325)
Log Population	-0.023	-0.120	-0.161	0.037	0.038	-0.040
	(0.032)	(0.113)	(0.135)	(0.093)	(0.125)	(0.137)
$\ln(y_{i,t-6})$	0.909***	0.386***	0.013			
	(0.040)	(0.048)	(0.068)			
$\ln(y_{i,t-10})$				0.524***	0.089	-0.082
				(0.046)	(0.072)	(0.083)
Constant	0.128	-0.595	-1.012	-0.341	-2.134**	-2.092
	(0.271)	(0.828)	(1.329)	(0.693)	(0.957)	(1.459)
Observations	632	632	494	617	617	479
R^2	0.997	0.973	0.968	0.980	0.971	0.971
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors are reported in parentheses and are clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (1)–(3) control for lagged GDP per capita at $t-6$ ($\ln(y_{i,t-6})$), while columns (4)–(6) control for lagged GDP capita at $t-10$ ($\ln(y_{i,t-10})$).

equipment price is a strong and statistically significant predictor of current income (Column 2, $\beta = -0.28$) and future income (Column 3, $\beta = -0.24$). However, its association with past income (Column 1, $\beta = -0.05$) is substantially smaller in magnitude. This asymmetry where prices strongly predict future growth but barely "predict" the past serves as a placebo test. Instead, favorable equipment prices appear to precede and propel subsequent economic takeoff.

Second, the results highlight a heterogeneity between capital asset types. While low equipment prices are consistently associated with higher income levels across specifications, the coefficients on structures price are largely insignificant or economically small. For example, in the concurrent specification (Column 2), the elasticity of equipment prices is nearly four times greater than that of structures price. This indicates that while high structure costs may depress investment volume (as established in Fact 2), they do not constitute the primary binding constraint on aggregate productivity and long-term development compared to the affordability of equipment.

Robustness Checks The results are robust to alternative specifications of the conditional convergence term. In the baseline estimation, we fixed the timing of the lagged income control (e.g., at $t-6$), which implies a varying time interval between the outcome and the control across different forecast horizons. To ensure that our findings are not driven by these varying lag lengths, we re-estimate the equation (2) in Appendix B.2.1 by maintaining a constant year gap (e.g., 5 years) between the dependent variable and the lagged GDP per capita:

$$\ln(y_{i,t+h}) = \beta^{h,\tau}_{\text{Equip}} \ln(P^{\text{Equip}}_{it}) + \beta^{h,\tau}_{\text{Str}} \ln(P^{\text{Str}}_{it}) + \mathbf{X}'_{it}\Gamma^{h,\tau} + \lambda^{h,\tau} \ln(y_{i,t+h-\tau})^h + \alpha^{h,\tau}_i + \delta^{h,\tau}_t + \epsilon^h_{it}$$

As shown in Table B.I, the dynamic asymmetry remains robust: equipment prices strongly predict current and future income levels but show little association with past income, confirming that the results are not an artifact of the convergence specification.

In addition, we verify the robustness of our results by replacing the point-in-time observations with smoothed measures based on centered moving averages. This approach is intended to mitigate measurement error and short-run business cycle fluctuations inherent in the PWT series. Specifically, for each selected benchmark year t, we construct the outcome variables and controls as a five-year centered average:

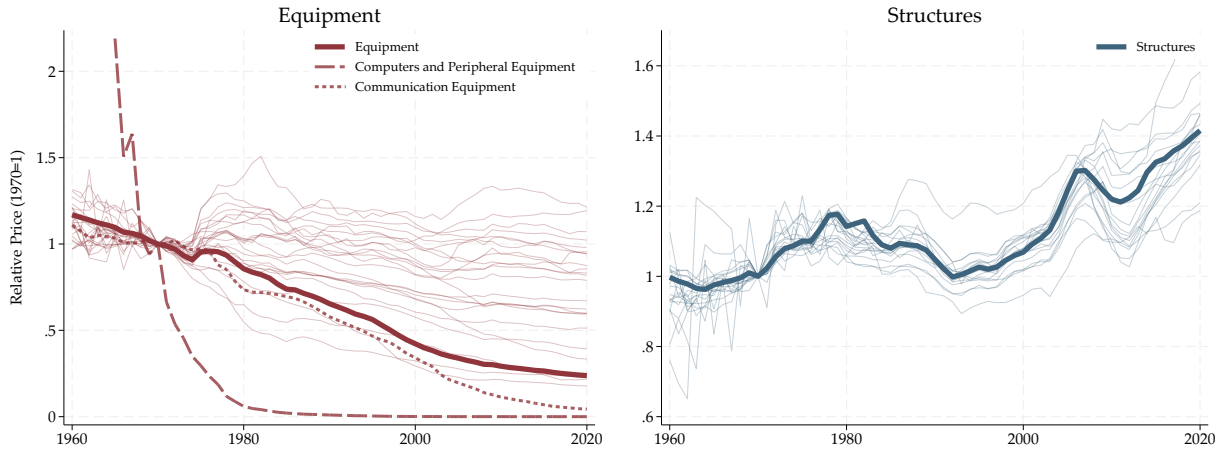
$$\bar{X}_{it} = \frac{X_{i,t-2} + X_{i,t-1} + X_{i,t} + X_{i,t+1} + X_{i,t+2}}{5}.$$

We implement this procedure for the ICP benchmark years (1996, 2005, 2011, 2017, and 2021) and additionally retain the 1990 and 2001 benchmarks to construct the necessary lag structures. The smoothed outcomes include the logarithm of GDP per capita and the (log) TFP index, while the baseline covariates comprise the human capital index, years of schooling, and log population. We find that using these moving-average outcomes yields estimates that are qualitatively similar to the baseline, indicating that our results are not driven by transitory noise in the level measures. The detailed results are reported in Appendix B.2.2.

Finally, in addition to GDP per capita, we examine to what extent capital prices in each sector are related to Total Factor Productivity (TFP) and find that lower equipment prices are associated with higher contemporaneous TFP, while structures price are positively related to TFP, highlighting strong heterogeneity in how different capital types affect productive efficiency. Results are reported in Appendix B.2.3.

Fact 4: In the U.S., the post-1970 decline in equipment prices was largely driven by computers and related items, whereas the post-1990 rise in structures price was broad-based across nearly all types of structures.

Figure 3: **Relative Investment Price Index Trend by Sector (1950-2020)**



Notes: The figure plots trends in relative investment prices by BEA asset type. For each asset category, an implicit price index is recovered from BEA data as nominal investment divided by the corresponding chain-type quantity index. The resulting series is deflated using the Consumer Price Index (CPI) and then normalized to 1 in 1970 for each category. The sample is restricted to 1960–2020. Thin lines show disaggregated categories, while thicker highlighted lines emphasize the aggregate equipment series and selected subcomponents (information processing equipment, computers and peripheral equipment, and communication equipment). *Sources:* U.S. Bureau of Economic Analysis (BEA), NIPA Table 2.7 and Table 2.8; Federal Reserve Bank of St. Louis (FRED), CPI for All Urban Consumers: All Items (CPIAUCSL); and authors' calculations.

We now narrow our focus to the United States and document the evolution of investment prices at the level of BEA asset types. Figure 3 highlights two contrasting patterns in relative investment prices across BEA asset categories. First, the relative price of equipment exhibits a sharp and persistent decline after 1970. This decline is not uniform across equipment categories; rather, it is concentrated in information-processing assets. In particular, computers and peripheral equipment display the steepest and most sustained price declines, while communication equipment shows similarly large reductions. Together, these two categories account for about 20% of total equipment investment, and the broader category of information-processing equipment represents roughly 35%. This concentration is consistent with rapid improvements in embodied technology and the associated quality-adjusted price declines emphasized in the investment-specific technological change literature (Jones, 1994; Byrne and Pinto, 2015; Lian et al., 2020).

Second, in sharp contrast, the relative price of structures rises markedly after 1990. Importantly, this increase is not driven by a single type of structure: the disaggregated structure series move upward together, indicating a broad-based rise across nearly all structure categories. This pattern suggests that post-1990 structures price dynamics are better characterized as an economy-wide shift affecting the structure component of in-

vestment rather than a compositional change within structures. These results are robust to using BEA price indices constructed from the current-cost net stock (capital stock) series for both sectors, reported in Appendix B.3.

3 The Model

Motivated by these findings, we develop an endogenous growth framework that disaggregates capital into equipment and structures. Building on Romer (1990), we adopt the Rivera-Batiz and Romer (1991) "lab-equipment" specification, in which capital is not only essential for final-goods production but also enters as an input in the R&D sector. Within this framework, we characterize the balanced growth path and show that an increase in the relative price of structures exerts a drag on long-run growth through two channels: it distorts capital accumulation and it tightens the resource constraint facing innovation.

3.1 Capital Accumulation and ISTC

The economy features two distinct capital stocks: equipment, denoted by K_E, and structures, denoted by K_S.

Let $I_E(t)$ and $I_S(t)$ denote investment expenditures in equipment and structures, respectively, measured in units of the final good (the *numeraire*). Following Greenwood et al. (1997), we introduce ISTC via $q_E(t)$ and $q_S(t)$, which capture the efficiency with which one unit of the final good is transformed into physical capital. The relative price of each capital good is therefore the inverse of its investment efficiency:

$$P_E(t) \equiv \frac{1}{q_E(t)}, \qquad P_S(t) \equiv \frac{1}{q_S(t)}. \tag{3}$$

Capital stocks evolve according to

$$\begin{aligned} \dot{K}_E(t) &= q_E(t)\, I_E(t) - \delta_E K_E(t), \\ \dot{K}_S(t) &= q_S(t)\, I_S(t) - \delta_S K_S(t), \end{aligned}$$

where δ_E and δ_S denote the depreciation rates for equipment and structures, respectively. Investment efficiency evolves exogenously at constant rates γ_E and γ_S:

$$\frac{\dot{q}_E(t)}{q_E(t)} = \gamma_E, \qquad \frac{\dot{q}_S(t)}{q_S(t)} = \gamma_S. \tag{4}$$

Equipment capital K_E is allocated between final-good production (K_E^Y) and R&D (K_E^R); structures K_S are allocated analogously. Market-clearing conditions for capital therefore requires

$$K_E(t) = K_E^Y(t) + K_E^R(t), \qquad K_S(t) = K_S^Y(t) + K_S^R(t).$$

3.2 Firms

3.2.1 Final-Goods Sector

A representative competitive firm produces the final good using equipment (K_E^Y), structures (K_S^Y), and unskilled labor (L_u). The production technology is Cobb-Douglas

$$Y(t) = A(t) \left(K_E^Y(t)\right)^{\alpha_E} \left(K_S^Y(t)\right)^{\alpha_S} \left(L_u(t)\right)^{1-\alpha_E-\alpha_S}. \tag{5}$$

Taking prices as given, the firm chooses inputs to maximize profits

$$\max_{K_E^Y, K_S^Y, L_u} \left\{ Y(t) - R_E(t)K_E^Y(t) - R_S(t)K_S^Y(t) - w_u(t)L_u(t) \right\}.$$

The first-order conditions imply factor prices equal marginal revenue products:

$$R_E(t) = \alpha_E \frac{Y(t)}{K_E^Y(t)}, \qquad R_S(t) = \alpha_S \frac{Y(t)}{K_S^Y(t)}, \qquad w_u(t) = \left(1-\alpha_E-\alpha_S\right) \frac{Y(t)}{L_u(t)}.$$

3.2.2 R&D Sector

The R&D sector produces new designs that drive the evolution of total factor productivity $A(t)$. The sector operates competitively and uses equipment capital (K_E^R), structures (K_S^R), and skilled labor (L_s). Knowledge production is given by

$$\dot{A}(t) = \kappa A(t)^{\phi} \left(K_E^R(t)\right)^{\eta_E} \left(K_S^R(t)\right)^{\eta_S} \left(L_s(t)\right)^{1-\eta_E-\eta_S}. \tag{6}$$

Let $A(t)$ denote the aggregate stock of knowledge and let $p_A(t)$ denote the (final good denominated) shadow value of a marginal increase in $A(t)$ for the representative household. In the baseline model, $A(t)$ does not generate direct payment stream in the household budget constraint and accordingly, $p_A(t)$ is a costate variable associated with $A(t)$. This interpretation is in the spirit of Jones and Williams (1998), who characterize the return to knowledge using the economy's production possibilities and interpret $p_A(t)$ as the

shadow value of the knowledge stock rather than the price of a traded claim.[10]

Since $A(t)$ augments production, its technological marginal product in the final-goods technology is

$$\frac{\partial Y(t)}{\partial A(t)} = \frac{Y(t)}{A(t)}. \tag{7}$$

This object is a technological marginal product. It enters the costate dynamics for $p_A(t)$, and it need not correspond to any payment made by firms to an owner of $A(t)$ in competitive equilibrium. The shadow value $p_A(t)$ evolves according to the costate equation

$$\dot{p}_A(t) = r(t)\, p_A(t) - \frac{\partial Y(t)}{\partial A(t)} = r(t)\, p_A(t) - \frac{Y(t)}{A(t)}. \tag{8}$$

In the competitive equilibrium described here, factor payments exhaust output in the final-goods sector. The term $Y(t)/A(t)$ should therefore be interpreted as the marginal product of $A(t)$ that appears in the evolution of the shadow value $p_A(t)$, not as a dividend on a traded knowledge asset.

In equilibrium, R&D decisions are disciplined by $p_A(t)$, the shadow value of knowledge; we use $p_A(t)$ as a device to summarize the marginal value of $A(t)$. The representative R&D firm maximizes current profits:

$$\max_{K_E^R, K_S^R, L_s} \left\{ p_A(t)\dot{A}(t) - R_E(t)K_E^R(t) - R_S(t)K_S^R(t) - w_s(t)L_s(t) \right\}.$$

The corresponding first-order conditions are

$$R_E(t) = \eta_E \frac{p_A(t)\dot{A}(t)}{K_E^R(t)}, \qquad R_S(t) = \eta_S \frac{p_A(t)\dot{A}(t)}{K_S^R(t)}, \qquad w_s(t) = \big(1 - \eta_E - \eta_S\big) \frac{p_A(t)\dot{A}(t)}{L_s(t)}.$$

3.3 Households

3.3.1 Population and Labor Supply

Population $N(t)$ grows at a constant exogenous rate n:

$$\dot{N}(t) = nN(t).$$

[10] In case of introducing an market for knowledge, the appropriate dividend in the no-arbitrage condition is the profit flow associated with a marginal patent, $\pi_A(t)$. Formally, the asset-pricing equation becomes $r(t)p_A(t) = \pi_A(t) + \dot{p}_A(t)$, where $\pi_A(t)$ is the profit flow accruing to the owner of a marginal design under an explicit licensing or monopolistic-competition microfoundation such as Romer (1990) and Jones (1995).

We normalize the labor endowment per capita to unity, such that total labor supply equals population size, $L(t) = N(t)$. A fixed fraction $s \in (0, 1)$ of the workforce supplies skilled labor to the R&D sector, while the remaining fraction $(1 - s)$ supplies unskilled labor to the final-goods sector:

$$L_s(t) = sN(t), \qquad L_u(t) = (1 - s)N(t).$$

In equilibrium, firms' labor demand is pinned down by wages and equals the sectoral labor supplies above.

3.3.2 Preferences

The representative household maximizes discounted lifetime utility from per-capita consumption $c(t) \equiv C(t)/N(t)$:

$$U_0 = \int_0^\infty e^{-\rho t} N(t) \, \frac{c(t)^{1-\sigma}}{1-\sigma} \, dt,$$

where $\rho > 0$ is the subjective discount rate and $\sigma > 0$ is the inverse of the intertemporal elasticity of substitution.

3.3.3 Budget Constraint and Euler Equation

Households own the economy's capital stock and rent it to firms, and they supply labor. Let $\Pi(t)$ denote aggregate firm profits rebated lump-sum to households. The aggregate budget constraint is

$$C(t) + I_E(t) + I_S(t) = w_s(t)L_s(t) + w_u(t)L_u(t) + r_E(t)K_E(t) + r_S(t)K_S(t) + \Pi(t).$$

The household's optimization implies the standard Euler equation:

$$\frac{\dot{c}(t)}{c(t)} = \frac{1}{\sigma}\big(r(t) - \rho\big),$$

where $r(t)$ is the real interest rate.

3.3.4 Optimal Savings and Arbitrage

Households allocate savings between financial assets yielding $r(t) = r_E(t) = r_S(t)$ and physical capital. No-arbitrage requires that the return on each capital type, including rental income, capital gains or losses, and depreciation, equals $r(t)$. Using $P_k(t) = 1/q_k(t)$ and $\dot{P}_k(t)/P_k(t) = -\gamma_k$, the no arbitrage conditions are

$$r(t) = \frac{R_E(t)}{P_E(t)} + \frac{\dot{P}_E(t)}{P_E(t)} - \delta_E = q_E(t)R_E(t) - \gamma_E - \delta_E, \tag{9}$$

$$r(t) = \frac{R_S(t)}{P_S(t)} + \frac{\dot{P}_S(t)}{P_S(t)} - \delta_S = q_S(t)R_S(t) - \gamma_S - \delta_S. \tag{10}$$

In equilibrium, the marginal product of each capital type in final-good production equals its user cost. Combining FOCs, we get

$$\alpha_E \frac{Y(t)}{K_E^Y(t)} = P_E(t)\big(r(t) + \delta_E + \gamma_E\big),$$
$$\alpha_S \frac{Y(t)}{K_S^Y(t)} = P_S(t)\big(r(t) + \delta_S + \gamma_S\big).$$

3.4 Balanced Growth Path (BGP) and the Structural Drag Mechanism

To ensure the existence of a stable BGP, we impose the standard semi-endogenous restriction (see Appendix C for the full derivation):

$$\Delta \equiv (1-\phi)(1-\alpha_E-\alpha_S) - (\eta_E + \eta_S) > 0. \tag{11}$$

On a BGP, aggregate quantities $(Y, C, I_E, I_S, K_E, K_S)$ grow at constant rates, and sectoral allocation shares remain constant. In particular, capital growth rates satisfy

$$g_{K_E} = g_Y + \gamma_E, \qquad g_{K_S} = g_Y + \gamma_S,$$

and, given the fixed labor allocation rule, labor in both sectors grows at the population rate,

$$\frac{\dot{L}_s}{L_s} = \frac{\dot{L}_u}{L_u} = n.$$

Log-differentiating the final-goods and innovation technologies yields the BGP sys-

tem:

$$g_Y = g_A + \alpha_E(g_Y + \gamma_E) + \alpha_S(g_Y + \gamma_S) + (1 - \alpha_E - \alpha_S)n, \tag{12}$$

$$(1 - \phi)g_A = (\eta_E + \eta_S)g_Y + \eta_E\gamma_E + \eta_S\gamma_S + (1 - \eta_E - \eta_S)n. \tag{13}$$

Solving (12) for g_Y delivers a decomposition:

$$g_Y = n + \underbrace{\frac{1}{1 - \alpha_E - \alpha_S}g_A}_{\text{TFP contribution}} + \underbrace{\frac{\alpha_E\gamma_E + \alpha_S\gamma_S}{1 - \alpha_E - \alpha_S}}_{\text{ISTC-induced deepening}}. \tag{14}$$

Substituting (14) into (13) yields the endogenous TFP growth rate:

$$g_A = \frac{(1 - \alpha_E - \alpha_S)n + \big(\eta_E(1 - \alpha_S) + \eta_S\alpha_E\big)\gamma_E + \big(\eta_S(1 - \alpha_E) + \eta_E\alpha_S\big)\gamma_S}{(1 - \phi)(1 - \alpha_E - \alpha_S) - (\eta_E + \eta_S)}. \tag{15}$$

Interpreting the structural drag mechanism. To highlight the role of ISTC imbalance, rewrite the numerator of (15) as

$$(1 - \alpha_E - \alpha_S) \cdot n + (\eta_E + \eta_S) \cdot \gamma_E - (\eta_S(1 - \alpha_E) + \eta_E\alpha_S) \cdot (\gamma_E - \gamma_S), \tag{16}$$

which makes explicit that $(\gamma_E - \gamma_S) > 0$ generates a negative "structural drag" term with weight

$$\omega_{\text{drag}} \equiv \eta_S(1 - \alpha_E) + \eta_E\alpha_S. \tag{17}$$

Relative to the one-capital benchmark (or the knife-edge case $\gamma_S = \gamma_E$), this term lowers the equilibrium innovation rate by limiting the extent to which rapid equipment ISTC translates into sustained idea growth. When structures enter the R&D technology and $\gamma_S < \gamma_E$ empirically, long-run innovation is depressed through two mechanisms that we refer to collectively as *R&D-related Structural Drag*. This R&D-related structural drag can be decomposed into two channels: a direct input channel and an indirect resource channel. First, the direct input channel reflects the fact that structures are a physical input in knowledge production: the coefficient on γ_S contains the term $\eta_S(1 - \alpha_E)$, so slower ISTC in structures raises the effective user cost of R&D facilities and directly reduces the growth rate of ideas.

Second, the indirect resource channel operates through the final-goods constraint. Even holding R&D input shares fixed, slower efficiency growth in structures depresses aggregate output growth and, through the induced slowdown in capital accumulation,

constrains the resources available to expand both K_E^R and K_S^R. In (16), this channel is captured by the component $\eta_E \alpha_S$ inside the coefficient on γ_S: technologically sluggish structures reduce the contribution of rapid equipment ISTC to innovation by tightening the resource constraint.

3.5 Comparison with the Standard One-Capital Model

To highlight the implications of capital heterogeneity, we compare our *Two-Capital Model* with the standard neoclassical *One-Capital Model*, which aggregates equipment and structures into a single capital stock K. In the one-capital benchmark, both the final-goods and R&D sectors use the same aggregate capital input, so the knowledge production function features *only one* capital term.

Formally, the one-capital environment can be interpreted as imposing a common ISTC process across capital types, $\gamma_S = \gamma_E \equiv \gamma$, aggregating capital shares $\alpha_{\text{one}} = \alpha_E + \alpha_S$, and collapsing R&D capital intensities to a single parameter $\eta_{\text{one}} \equiv \eta_E + \eta_S$.

Under this restriction, the BGP system implies the familiar semi-endogenous growth expression:

$$g_A^{\text{one}} = \frac{(1-\alpha_{\text{one}})n + \eta_{\text{one}}\gamma}{(1-\phi)(1-\alpha_{\text{one}}) - \eta_{\text{one}}}. \tag{18}$$

Output growth satisfies

$$g_Y^{\text{one}} = n + \frac{g_A^{\text{one}} + \alpha_{\text{one}}\gamma}{1-\alpha_{\text{one}}}. \tag{19}$$

Table 3 summarizes the analytic solutions for (g_A, g_Y) in the two models.

Table 3: **Analytical Comparison of BGP Growth Rates**

Model	**One-Capital Model**	**Two-Capital Model**
TFP Growth (g_A)	$\frac{(1-\alpha_{\text{one}})n + \eta_{\text{one}}\gamma}{(1-\phi)(1-\alpha_{\text{one}}) - \eta_{\text{one}}}$	$\frac{(1-\alpha_E-\alpha_S)n + (\eta_E(1-\alpha_S)+\eta_S\alpha_E)\gamma_E + (\eta_S(1-\alpha_E)+\eta_E\alpha_S)\gamma_S}{(1-\phi)(1-\alpha_E-\alpha_S) - (\eta_E+\eta_S)}$
GDP per capita Growth ($g_{Y/L}$)	$\frac{g_A^{\text{one}} + \alpha_{\text{one}}\gamma}{1-\alpha_{\text{one}}}$	$\frac{g_A + \alpha_E\gamma_E + \alpha_S\gamma_S}{1-\alpha_E-\alpha_S}$

Notes: This table compares closed-form balanced-growth-path growth rates across the one-capital and two-capital models. The expressions show how population growth n and exogenous knowledge-growth terms (γ or γ_E, γ_S) map into g_A and $g_{Y/L}$ through spillover elasticities (the η's) and factor shares (the α's), with $(1-\phi)$ governing the strength of scale effects.

The divergence between the two models is driven by heterogeneity in ISTC across capital types. In the one-capital model, aggregation eliminates any relative-price wedge by structures: all investment benefits from the same efficiency growth rate γ, and R&D uses

a single composite capital input. By contrast, in the two-capital model with $\gamma_E > \gamma_S$, sluggish structures ISTC lowers the equilibrium innovation rate via a structural drag component that is proportional to the ISTC gap $(\gamma_E - \gamma_S)$, with coefficient ω_{drag} (defined in equation (17)); that is, the drag enters as $-\omega_{\text{drag}}(\gamma_E - \gamma_S)/\Delta$. This effect operates through (i) a direct increase in the effective user cost of structures used in R&D and (ii) an indirect tightening of the economy-wide resource constraint, which attenuates the extent to which rapid equipment ISTC translates into sustained idea growth. Consequently, the one-capital model suffers from aggregation bias: it imputes the fast efficiency gains of equipment to the entire capital stock and overlooks the bottleneck created by slowly improving structures, thereby overstating long-run innovation and output growth relative to the two-capital economy.

4 Quantitative Analysis

4.1 Calibration

We calibrate the model to match U.S. long-run moments and parameter estimates from the literature, using transparent mappings from data to model objects. In particular, we construct the exogenous trends that pin down the BGP by targeting population growth and ISTC.

The population growth rate n is set to the average growth rate of total population in the PWT from 1970 to 2020. We proxy sectoral ISTC with relative-price trends in PWT: the equipment ISTC rate γ_E is set to the average annual decline in the relative price of equipment, while the structures ISTC rate γ_S is set analogously using the relative price of structures. Over our sample, from 1970 to 2020, this implies around $\gamma_E = 0.03$ and $\gamma_S = -0.01$, consistent with a rapidly falling relative price of equipment and a rising relative price of structures.

On the production side, we calibrate the Cobb-Douglas factor elasticities by combining information on the aggregate labor income share and the composition of the investment. Using the PWT Labor Detail report, we set the labor income share to 0.62, which implies an aggregate capital share of 0.38, reported in 2015. We then split this aggregate capital share between equipment and structures using the U.S. average share of equipment within the total investment from the PWT Capital Detail data. Specifically, the equipment share is 0.39, so that the output elasticity of equipment is calibrated to $\alpha_E = 0.15$, while the output elasticity of structures is calibrated to $\alpha_S = 0.23$. We use this investment compo-

sition as a simple empirical proxy to split the aggregate capital income share across asset types.[11]

Turning to the innovation block, we set the intertemporal knowledge-spillover parameter to $\phi = -2.0$ following Bloom et al. (2020). We discipline the Cobb-Douglas input elasticities in the R&D production function using factor-share evidence from the National Center for Science and Engineering Statistics (NCSES) Business Enterprise Research and Development (BERD) data (Égert, 2016; Moretti et al., 2025). Using the BERD surveyed in 2015, we set the labor share in R&D to 0.67, which implies an R&D capital share of 0.33. We allocate this R&D capital share across equipment and structures using the observed equipment share in R&D capital spending, 0.79, which implies that equipment accounts for $\eta_E = 0.26$ of the R&D technology, while structures accounts for the remaining $\eta_S = 0.07$.[12]

Table 4 reports the full set of calibrated parameters used in the numerical analysis.

Table 4: **Calibration of Parameters for the U.S. Economy**

Symbol	Description	Value	Source
	Demographics & Labor		
n	Population growth rate	0.0098	PWT (1970–2020)
	ISTC		
γ_E	Inverse relative price growth of Equipment (TFP)	0.0290	PWT (1970–2020)
γ_S	Inverse relative price growth of Structures (TFP)	−0.0101	PWT (1970–2020)
	Production Technology		
α_E	Share of Equipment in Output	0.1469	PWT (2015)
α_S	Share of Structures in Output	0.2312	PWT (2015)
	R&D Sector Parameters		
ϕ	Knowledge spillover parameter	−2.0	Bloom et al. (2020)
η_E	Share of Equipment in R&D	0.2607	BERD (2015)
η_S	Share of Structures in R&D	0.0699	BERD (2015)

Notes: The model is calibrated at annual frequency. Table summarizes the baseline parameterization for the U.S. economy. Together, these values discipline the balanced-growth implications used in the quantitative exercises.

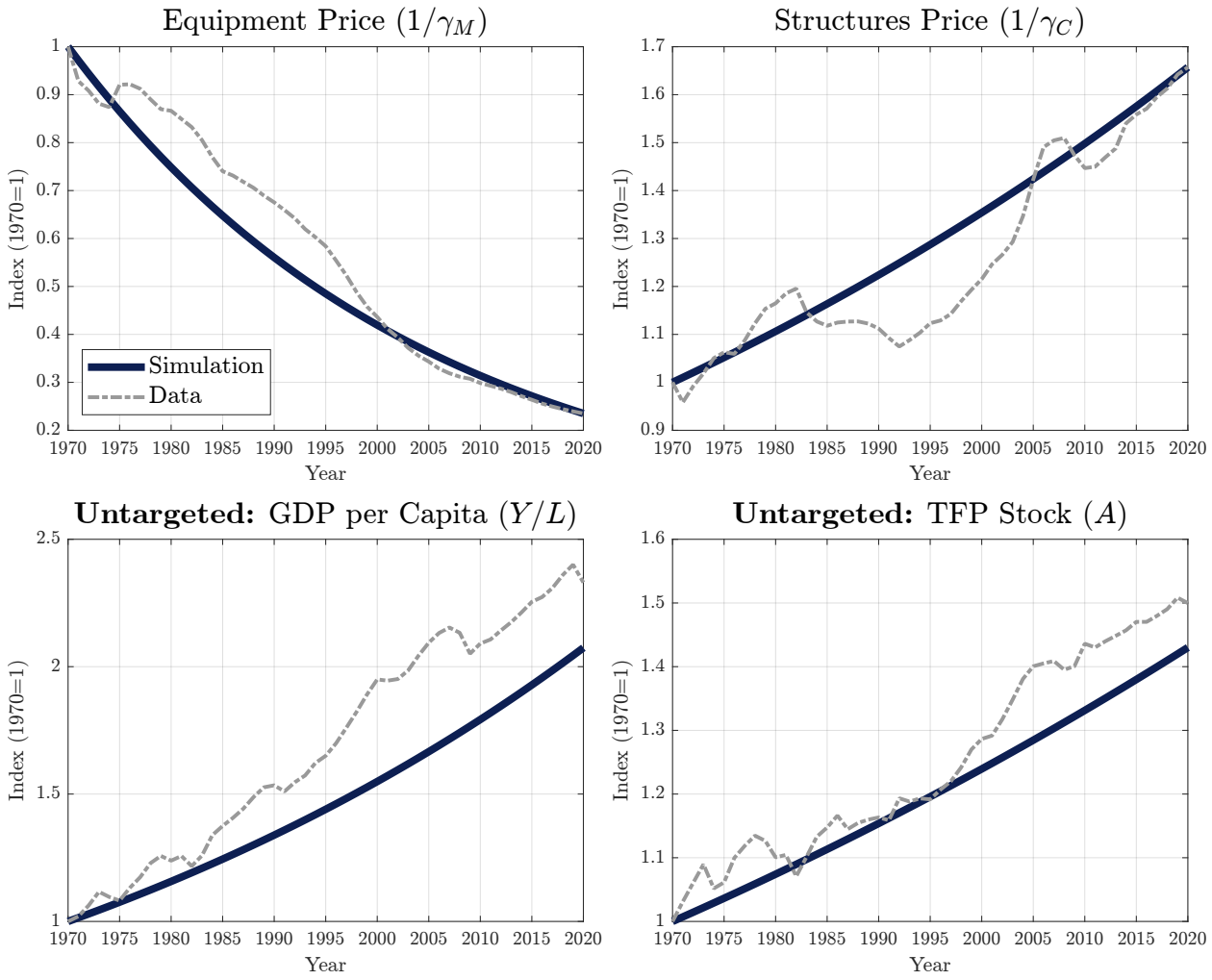
[11] Along the balanced growth path, investment-flow composition can be derived as $\frac{I_E/I_S}{\alpha_E/\alpha_S} = \frac{g_Y+\delta_E}{g_Y+\delta_S} \cdot \frac{r+\delta_S}{r+\delta_E}$. Under our calibration ($\delta_E = 0.13$, $\delta_S = 0.03$, $g_Y = 0.0244$, $r = 0.03$), this ratio is approximately 1.06, so the implied I_E/I_S is close to α_E/α_S.

[12] Analogously, we use the observed composition of R&D capital spending as an external proxy to allocate the aggregate R&D capital share across equipment and structures.

4.2 Model Performance

We first evaluate the calibrated model's ability to replicate the growth trajectory of the United States from 1970 to 2020. Subsequently, we analyze the quantitative impact of the structural drag on long-run growth. Figure 4 compares the simulated series with empirical data.

Figure 4: **Baseline Simulation: Sectoral Prices and Macroeconomic Aggregates**



Notes: The top panels show the targeted moments: the relative prices of equipment ($1/q_E$) and structures ($1/q_S$), which the simulation is calibrated to match. The bottom panels show untargeted moments: GDP per capita (Y/N) and the TFP stock (A). The sectoral relative price series and GDP per capita are taken from the Penn World Table (PWT), while the TFP stock is obtained from the Bureau of Labor Statistics (BLS) (Private Business Sector: Total Factor Productivity (`MFPPBS` in FRED)). All series are normalized to 1 in 1970.

Targeted Moments: Sectoral Prices The top panels of Figure 4 show the relative prices of equipment ($1/q_E$) and structures ($1/q_S$). These series are the primary exogenous drivers

of the model, with γ_E and γ_S calibrated to match the empirical trends. The simulation closely tracks the steady decline in equipment costs and the secular rise in structures price, reflecting the ISTC imbalance observed in the U.S. data.

Untargeted Moments: GDP per capita and TFP The bottom panels present the results for untargeted moments: GDP per capita (Y/L) and the TFP stock (A). The empirical benchmarks are sourced from the PWT and the Bureau of Labor Statistics (BLS), respectively. The calibrated model closely closely matches the observed growth paths of GDP per capita and the TFP stock.

4.2.1 Sensitivity Analysis

We conducted a sensitivity analysis to assess the robustness of our model across different parameter settings, particularly ϕ. The candidates for ϕ values are drawn from Jones (2022).[13] Table 5 summarizes the steady-state growth rates of technology, g_A, and output per capita, $g_{Y/L}$, calculated for each ϕ.

Table 5: **Growth Rates Under Various Values of ϕ**

ϕ	g_A	$g_{Y/L}$
0	0.0377	0.0637
−1	0.0120	0.0224
−2 (benchmark)	0.0072	0.0146
−4	0.0040	0.0094

Notes: This table reports the implied balanced-growth rates of TFP, g_A, and labor-productivity, $g_{Y/L}$, as the knowledge-spillover parameter ϕ varies. More negative values of ϕ reduce the strength of effective spillovers (equivalently, increase the degree of diminishing returns in research), lowering both g_A and $g_{Y/L}$. The candidates for ϕ are taken from Jones (2022).

As shown in Table 5, the growth rates of both technology and output per capita are highly sensitive to the value of ϕ, which represents the returns to the existing stock of knowledge. When ϕ increases from −4 toward 0, we observe a significant acceleration in growth. For instance, the technology growth rate (g_A) at $\phi = 0$ is nearly ten times higher than that at $\phi = -4$.

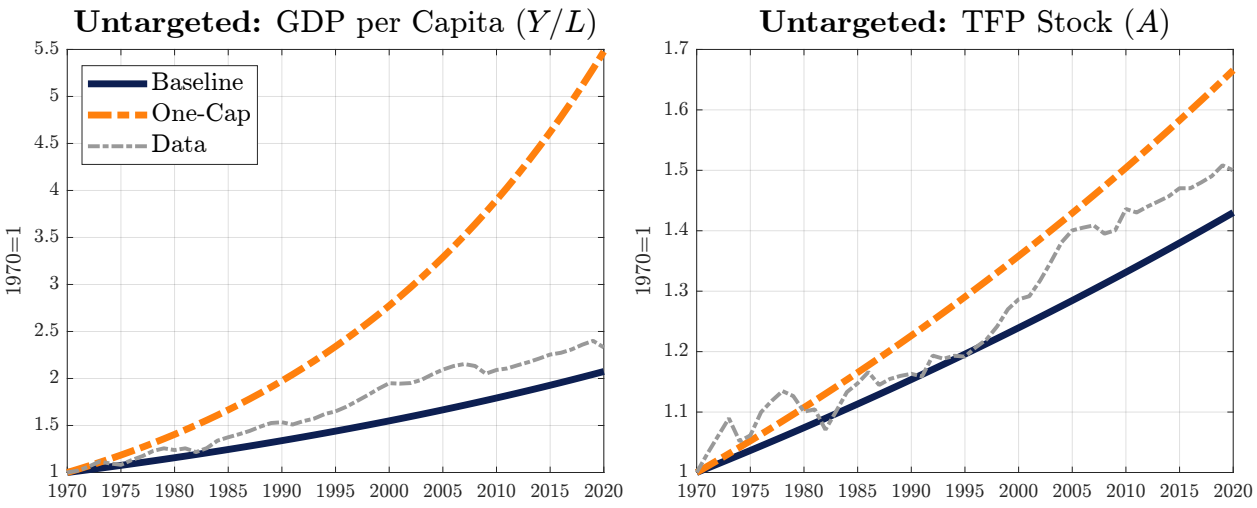
[13]We impose a technical restriction on the parameter range to ensure the model's structural integrity. Specifically, following Jones (2022), we can match ϕ with β in Jones (2022) by $\phi \equiv 1 - \beta$. We note that the case where $\beta = 0.2$ (which implies $\phi = 0.8$) is excluded from our analysis as it violates the fundamental regularity condition of our model, $\Delta > 0$ (defined in equation 11).

4.2.2 Comparison with the One-Capital Model

To illustrate the importance of distinguishing between equipment and structures, Figure 5 compares our baseline results with a counterfactual One-Capital Model (indicated by the orange dashed line). In this alternative specification, we assume that all capital goods share the same investment efficiency growth as equipment ($\gamma_S = \gamma_E$), effectively ignoring the structural drag of the structures sector.

As shown in the Figure 5, the One-Capital Model significantly overestimates both GDP per capita and TFP growth. Specifically, by 2020, the One-Capital Model predicts a level of GDP per capita nearly double the observed data. This "jump" in the growth trajectory occurs because the standard model treats the entire capital stock as if it benefits from the rapid technological frontier of information technology and equipment. By contrast, our baseline model (solid blue line) is much closer to the empirical data by accounting for the rising relative cost of structures. This comparison confirms that the secular stagnation observed in the U.S. is not due to a lack of equipment innovation, but rather due to the bias inherent in One-Capital frameworks that overlook the severe productivity bottleneck in the structures sector.

Figure 5: **Baseline vs. One-Capital Model Comparison**



Notes: The blue solid line represents the baseline model with two types of capital. The orange dashed line represents the One-Capital model (labeled "One-Cap") where the efficiency of structures is assumed to grow at the same rate as equipment ($\gamma_S = \gamma_E$). The gray dashed lines of each panel plots the actual trend. The sectoral relative price series and GDP per capita are taken from the Penn World Table (PWT), while the TFP stock is obtained from the Bureau of Labor Statistics (BLS) (Private Business Sector: Total Factor Productivity (`MFPPBS` in FRED)). All series are normalized to 1 in 1970.

4.3 Structural Drag Effect on Growth

To quantify the long-run impact of structural drag, we decompose balanced-growth per-capita output growth. Combining (14) with the closed-form expression for g_A in (15), and defining per-capita output growth as $g_y \equiv g_Y - n$, yields the linear representation

$$g_y = \mu_n^y \cdot n + \mathcal{M}_E \cdot \gamma_E + \mathcal{M}_S \cdot \gamma_S. \tag{20}$$

The coefficients in (20) are interpretable multipliers that map observed trend components into long-run per-capita growth. Grouping terms by n, γ_E, and γ_S implies

$$\mu_n^y \equiv \frac{1}{\Delta}, \qquad \mathcal{M}_E \equiv \frac{\alpha_E}{\Psi} + \frac{\eta_E(1-\alpha_S)+\eta_S\alpha_E}{\Psi\,\Delta}, \qquad \mathcal{M}_S \equiv \frac{\alpha_S}{\Psi} + \frac{\eta_S(1-\alpha_E)+\eta_E\alpha_S}{\Psi\,\Delta}, \tag{21}$$

where $\Psi \equiv 1-\alpha_E-\alpha_S$ and $\Delta \equiv (1-\phi)\Psi - (\eta_E+\eta_S)$ as in (11). A finite and stable BGP requires $\Delta > 0$.

Per-capita output growth can be decomposed into three parts. The population growth multiplier $\mu_n^y \equiv 1/\Delta$ captures a pure R&D scale (induced-innovation) effect (Romer, 1990; Jones, 1995). The equipment ISTC term, $\mathcal{M}_E\gamma_E$, captures the equipment contribution. When $\gamma_E > 0$, equipment efficiency growth raises per-capita output growth through capital deepening and, in the two-capital model, through induced innovation. The structure term, $\mathcal{M}_S\gamma_S$, captures the structures contribution. When structures ISTC is sluggish or negative, as in the U.S. case, this term turns negative and depresses long-run per-capita growth.

Each multiplier $\mathcal{M}_k$ has a transparent two-part structure. The terms α_k/Ψ capture the static capital-deepening channel through the final-goods technology. The remaining terms, proportional to $1/(\Psi\Delta)$, capture the induced-innovation channel that operates through the equilibrium idea-growth response embedded in (15).

Focusing on the structures contribution, we can rewrite $\mathcal{M}_S$ as the sum of three interpretable components: (i) capital deepening in final-goods production, (ii) the direct cost of structures used as R&D facilities, and (iii) an indirect resource-allocation channel that operates through the economy-wide constraint on innovation:

$$\mathcal{M}_S = \underbrace{\frac{\alpha_S}{\Psi}}_{\text{Static Deepening}} + \underbrace{\underbrace{\frac{\eta_S(1-\alpha_E)}{\Psi\,\Delta}}_{\text{Direct Input Channel}} + \underbrace{\frac{\eta_E\alpha_S}{\Psi\,\Delta}}_{\text{Indirect Resource Channel}}}_{\text{R\&D-related Structural Drag}}. \tag{22}$$

A decline in structures ISTC, i.e., a lower γ_S, reduces growth not only by lowering output and weakening incentives for capital accumulation in the final-goods sector (the static-deepening component), but also by increasing R&D-related structural drag through two mechanisms: it raises the effective user cost of structures required for R&D activity (the direct input channel) and, through the general-equilibrium resource constraint, tightens the economy-wide availability of resources for innovation (the indirect resource channel). Equation (22) quantifies the contribution of each channel to the overall drag. In particular, the term $\eta_S(1-\alpha_E)/(\Psi\Delta)$ captures the direct input channel because it is proportional to η_S and therefore arises only when structures enter the R&D technology as an input (e.g., facilities). The term $\eta_E\alpha_S/(\Psi\Delta)$ captures the indirect resource channel because it loads on α_S: changes in structures affect aggregate production incentives and, via the final-goods resource constraint, the equilibrium scale of research inputs.

Under the U.S. calibration, we decompose balanced-growth per-capita output growth by applying (20) together with the structures-channel split in (22). Table 6 reports the resulting contributions in percentage points (pp) per year.

Table 6: **U.S. Per-Capita Output Growth g_y Decomposition**

Component	Growth rate (pp/year)	Share of g_y (%)
Population ($\mu_n^y n$)	0.64	43.8
Equipment Boost ($\mathcal{M}_E\gamma_E$)	1.32	90.4
Structural Drag ($\mathcal{M}_S\gamma_S$)	-0.50	-34.2
Total g_y	**1.46**	**100.0**

Notes: This table decomposes U.S. per-capita output growth, g_y, into three additive components. The population term, $\mu_n^y n$, captures the contribution of population growth scaled by the model-implied multiplier. The equipment component, $\mathcal{M}_E\gamma_E$, measures the positive contribution from equipment-specific investment technology improvement, while the structures component, $\mathcal{M}_S\gamma_S$, captures the effect of structures-specific price changes, which is negative in the U.S. calibration. "Share of g_y" reports each component divided by total g_y; because the structures term is negative, shares can exceed 100 percent in absolute value.

Per-capita output growth is $g_y = 1.46$ pp per year. This growth reflects contributions from the population term (0.64 pp) and, in particular, equipment-specific ISTC (1.32 pp). By contrast, structures reduce growth by 0.50 pp, which is about 38% of the equipment boost in magnitude.

As shown in Table 7, the structural drag decomposes into a static-deepening component of −0.38 pp and R&D-related structural drag of −0.12 pp. This R&D-related structural drag is split almost evenly across the two channels implied by equation (22): the direct input channel accounts for 49.7% (−0.06 pp) and the indirect resource channel accounts for 50.3% (−0.06 pp). The near-equal split indicates that both mechanisms con-

Table 7: **U.S. Structural Drag: Channel Decomposition**

Component	Growth rate (pp/year)	Share of Structural Drag (%)	Share of R&D Drag (%)
Structural drag $\mathcal{M}_S\gamma_S$	-0.50	100	—
Static Deepening $\frac{\alpha_S}{\Psi}\gamma_S$	–0.38	74.9	—
R&D-related Structural Drag	-0.12	25.3	100
Direct Channel $\frac{\eta_S(1-\alpha_E)}{\Psi\Delta}\gamma_S$	-0.06	12.5	49.6
Indirect Channel $\frac{\eta_E\alpha_S}{\Psi\Delta}\gamma_S$	-0.06	12.7	50.4

Notes: Shares in the third column are computed relative to the total structures contribution, $\mathcal{M}_S\gamma_S$. Shares in the last column are computed relative to the R&D-related structural drag component. The *direct input channel* corresponds to the term $\eta_S(1-\alpha_E)/(\Psi\Delta)\gamma_S$ and captures the increase in the effective user cost of structures used as an input into R&D activity (e.g., research facilities) when structures ISTC is weak. The *indirect resource channel* corresponds to the term $\eta_E\alpha_S/(\Psi\Delta)\gamma_S$ and captures the general-equilibrium effect whereby weak structures efficiency growth tightens the final-goods resource constraint and reduces the equilibrium scale of research inputs. Negative growth rates indicate a drag on per-capita output growth.

tribute materially to overall structural drag.

4.4 Construction Productivity and Measurement Error Adjustment

A rapid increase in the price of structures after 1990 is consistent with a decline in construction productivity in the U.S. during the same period. Goolsbee and Syverson (2023) document that, while U.S. aggregate productivity (measured in value-added per worker) doubled between 1970 and 2020, it simultaneously fell by 40 percent for the construction sector. We find that the Bureau of Labor Statistics (BLS)'s productivity growth estimates for the construction sector are negative on average, −0.55%, per year over the 1987 to 2024 period, while productivity growth averaged 0.89% per year for the private business sector.[14]

Several factors may have contributed to stagnated construction productivity. For example, Goolsbee and Syverson (2023) showed that construction firms' abilities to turn materials into output has deteriorated and there is little reallocation from low productivity places to high-productivity places. D'Amico et al. (2024) find that the post-1970 productivity decline coincides with increases in proxies for land-use regulation. Local land-use controls limit the size of building projects, reducing both scale economies and

[14]The annual average productivity growth from 1987 to 2024 is 1.18% for Agriculture, 1.51% for Mining, 0.67% for Utilities, 1.15% for Durable manufacturing sector, 0.09% for Nondurable manufacturing sector, 1.10% for Trade, 0.58% for Transportation and warehousing, 1.01% for Information, -0.03% for Finance, insurance, real estate, and leasing, and 0.23% for Services.

incentives to invest in innovation.[15]

Still, a concern is that the secular rise in the relative price of structures may partly reflect deflator mismeasurement rather than a true decline in construction productivity.[16] Even though Goolsbee and Syverson (2023) conclude that the poor performance (of construction sector) is not just a figment of measurement error, structures price index from the PWT may have missed quality improvement of structures.[17]

Garcia and Molloy (2025) assess the extent to which growth in construction costs could be biased upward by improvements in unobserved structure quality.[18] We borrow their estimated range of bias and revisit the size of structural drag. Specifically, Garcia and Molloy (2025) quantify the bias using three different approaches. First, they use detailed industry construction cost data from R.S. Means to estimate the change in construction costs for specific housing types. This approach yields close to zero bias. Second, they obtain an assessment of structure quality from property tax assessors, a rating of structure quality from the resident of the home, and an estimate of energy efficiency. This approach yields 0.50 percentage points per year bias. Third, they apply an econometric technique for assessing the magnitude of unobserved variable bias (Oster, 2019). This approach yields the upper bound of 0.8 percentage points per year bias.

We impose a conservative upper bound of 0.8 pp per year on the bias in aggregate construction productivity growth. In our calibration, structures ISTC is proxied by the relative-price trend, which implies 1 pp. Under this upper bound, at most 80% of the implied structures-price growth can be attributed to measurement error, leaving the remaining roughly 20% to reflect a genuine decline in productivity.

In terms of growth contributions, the baseline structural drag is $\mathcal{M}_S\gamma_S = 0.50$ pp. The upper-bound correction reduces this drag by 0.40 pp, leaving a residual structural drag of about 0.10 pp. Thus, measurement error can attenuate, but cannot eliminate, the quantitative importance of structural drag.

[15] Productivity problem also appears in the public sector. Brooks and Liscow (2023) find that spending per mile in the Interstate Highway System increased more than threefold from the 1960s to the 1980s.

[16] Several authors have documented potential biases in the International Comparison Program; see, e.g., Deaton and Heston (2010) and Argente et al. (2023).

[17] The analysis in Goolsbee and Syverson (2023) control for quality changes by accounting for changes in housing size, but this adjustment alone could be insufficient, as it does not account for other aspects of quality.

[18] Their conclusion is that even under generous assumptions, their estimates of the magnitude of the bias are not large enough to alter the view that construction-sector productivity growth has been weak.

4.5 Counterfactual Analysis: Quantifying Structural Drag

To quantify the extent to which U.S. long-run growth has been hindered by the rising relative cost of structures, we conduct a counterfactual exercise benchmarking the United States against two reference groups: the median High-Income and median Low-Income economies, as classified in Section 2.2.

Table 8 summarizes the observed ISTC profiles. While equipment ISTC, γ_E, remains a robust driver of growth across all groups, structures ISTC ,γ_S, exhibits a stark divergence. Notably, the U.S. displays substantially more adverse structures ISTC (−1.01%) than the High-Income median (−0.42%), indicating a distinctive "structural drag" in the U.S. economy.

Table 8: **Observed ISTC Rates by Region (1970–2020)**

Region	Equipment (γ_E)	Structures (γ_S)	Gap ($\gamma_E - \gamma_S$)
Low Income	1.66%	−0.08%	1.74pp
High Income	3.02%	−0.42%	3.44pp
The United States	2.90%	−1.01%	3.91pp

Notes: ISTC rates are measured as the negative of the average growth rate of relative investment prices for equipment and structures over 1970–2020. The last column reports the implied ISTC gap between equipment and structures. Median LIC/HIC trends are taken from Figure 2.

To translate these differences into aggregate performance, we map the empirical ISTC rates into the calibrated growth-accounting framework in (21). Specifically, we feed the region-specific ISTC pairs from Table 8 into the U.S.-calibrated model as alternative shocks, holding the multipliers fixed at their U.S. values ($\mathcal{M}_E = 0.46$, $\mathcal{M}_S = 0.50$). Table 9 reports the implied growth contributions from ISTC.

Table 9: **Counterfactual U.S. Growth under Alternative ISTC Shocks**

Shock Scenario	Equipment Boost	Structural drag	g_y^{ISTC}
LIC Scenario	0.76pp	−0.04pp	0.72pp
HIC Scenario	1.38pp	−0.21pp	1.17pp
The United States	1.32pp	−0.50pp	0.82pp

Notes: Each row reports the implied per-capita output growth contribution from ISTC, g_y^{ISTC}, under alternative relative-price (ISTC) shock profiles. The "Equipment Boost" and "Structural drag" columns decompose g_y^{ISTC} into the contributions associated with equipment and structures ISTC, respectively. LIC (HIC) scenarios apply the observed low-income (high-income) ISTC rates to the U.S. calibration, while the last row reports the baseline U.S. benchmark.

These counterfactuals deliver two key insights. First, relative to the High-Income me-

dian, the U.S. growth shortfall is driven almost entirely by the structures margin. The equipment contribution is nearly identical (1.32pp vs. 1.38pp), but the U.S. experiences a much more severe structural drag (−0.50pp vs. −0.21pp). Second, relative to the Low-Income median, the U.S. outcome reflects offsetting forces: a larger equipment contribution (1.32pp vs. 0.76pp) is partly offset by a substantially more negative structures contribution.

To further characterize this drag, Table 10 decomposes the total structures contribution, $\mathcal{M}_S\gamma_S$, into (i) static capital deepening and (ii) an R&D-related structural drag component that aggregates the direct input and indirect resource channels in equation (22).

Table 10: **Decomposition: U.S. Baseline vs. LIC Counterfactual**

Component	U.S. Baseline (pp)	LIC Counterfactual (pp)	Δ pp
Structural Drag ($\mathcal{M}_S\gamma_S$)	-0.502	-0.040	+0.462
Static Deepening $\frac{\alpha_S}{\Psi}\gamma_S$	-0.375	-0.030	+0.345
R&D-related Structural Drag	-0.127	-0.010	+0.117

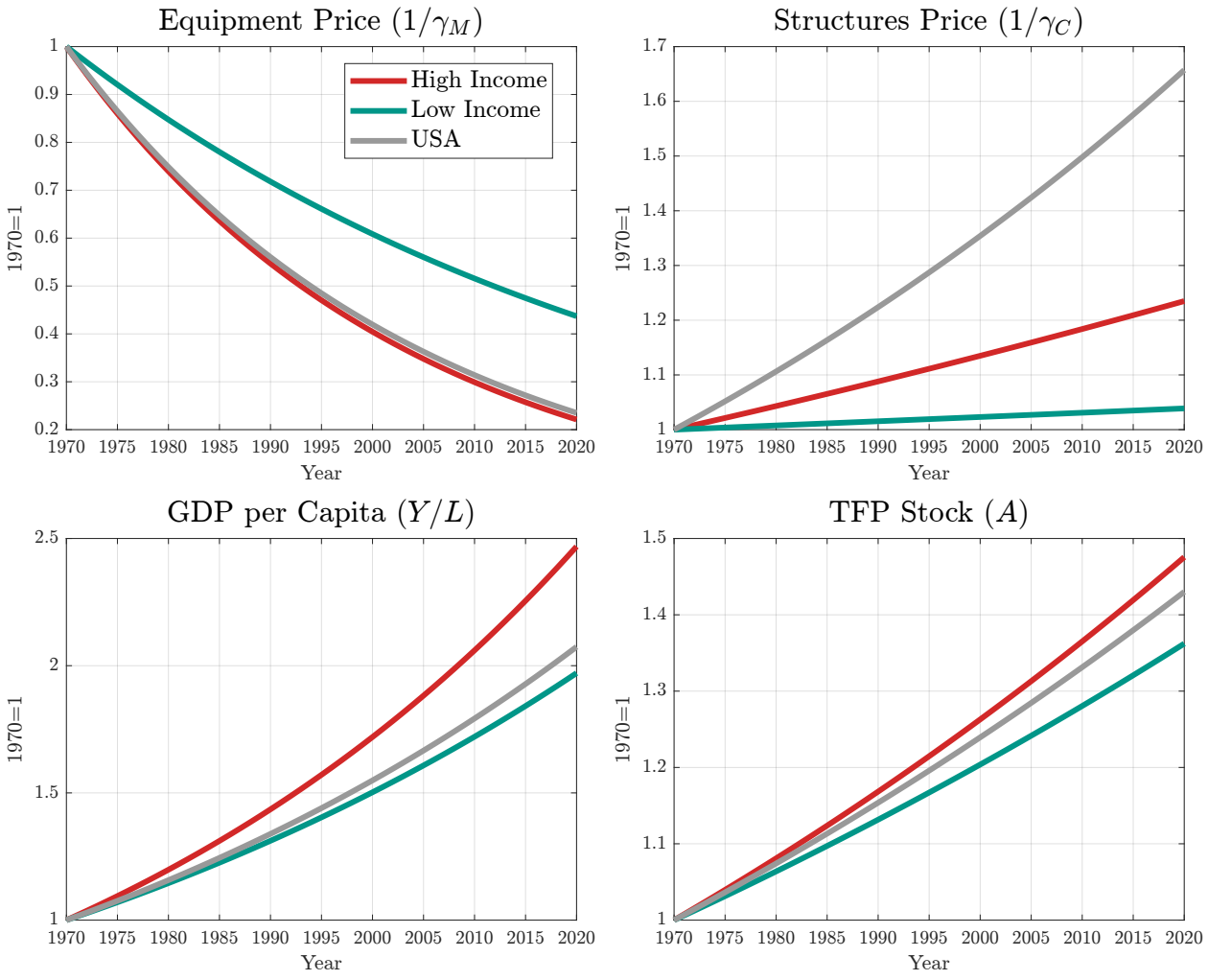
Notes: This table contrasts the structures-related contribution to U.S. per-capita output growth in the baseline calibration with a counterfactual that replaces the U.S. structures ISTC rate with the LIC value. The last column reports the change in percentage points for each component. The total structures term $\mathcal{M}_S\gamma_S$ is decomposed into (i) static capital deepening and (ii) an R&D-related structural drag component, which combines the direct input and indirect resource channels from equation (22).

If the U.S. had instead faced the LIC structures ISTC rate ($\gamma_S = -0.08\%$), per-capita growth would have been higher by 0.46 pp per year. Of this improvement, 0.12 pp comes from a smaller R&D-related structural drag component. In the baseline calibration, weak structures ISTC raises the effective cost of research infrastructure and, through general-equilibrium resource reallocation, reduces the equilibrium scale of research inputs. Under the LIC scenario, these R&D-related wedges are substantially attenuated, indicating that sluggish structures ISTC can act as a quantitatively meaningful constraint on sustained productivity growth.

Figure 6 visualizes these dynamics. The U.S. (gray) and High-Income (green) scenarios share similar equipment paths, but the divergence in structures ISTC causes the U.S. GDP per capita to fall behind. While the U.S. remains above the Low-Income (red) level due to its equipment efficiency, structural drag remains the primary obstacle preventing the U.S. from reaching the growth potential implied by the High-Income benchmark.

Taken together, these results show that the efficiency gap ($\gamma_E - \gamma_S$) is a useful summary measure of structural drags, but it does not fully characterize cross-group differences in outcomes. When comparing the United States to other High-Income economies, the shortfall is accounted for mainly by the structures margin, consistent with a sizable

Figure 6: **Transitional Paths under Alternative ISTC Regimes, 1970–2020**



Notes: The figure plots model-implied time paths when the economy is calibrated to the U.S. parameterization (including the U.S. multipliers) and is subjected to alternative ISTC shocks. The High-Income and Low-Income shock pairs (γ_E, γ_S) are taken from Table 8, while all other parameters are held fixed at their U.S.-calibrated values. The gray line corresponds to the U.S. shock pair, and the green and red lines apply the High-Income and Low-Income shock pairs, respectively. The top-left panel reports the equipment relative investment price index P_E and the top-right panel reports the structures relative investment price index P_S, both normalized to 1970=1. The bottom-left panel reports GDP per capita, and the bottom-right panel reports TFP (knowledge stock) A, each normalized to 1970=1.

"structural drag." By contrast, relative to Low-Income economies, differences in equipment ISTC remain quantitatively important, so aggregate performance reflects both an equipment boost and a structural drag. In the model, the structural drag operates through two channels: (i) it dampens capital deepening in final-goods production and (ii) it raises the effective cost of research infrastructure, thereby reducing the rate of innovation.

4.6 Extension: CES Technology Case

The key structural drag weight, ω_{drag}, is derived under the benchmark case in which both the final-goods and R&D sectors feature Cobb-Douglas technologies, implying a unit elasticity of substitution between equipment and structures. Extending the model to CES aggregation allows the effective drag to become state-dependent and potentially larger than in the benchmark. In particular, when the two capital types are complements (i.e., the elasticity of substitution is below one), sluggish structural ISTC translates more strongly into a drag.[19]

In each sector $j \in \{Y, R\}$, define capital services Q_j via a CES aggregator

$$Q_j(K_E^j, K_S^j) = \left(\theta_j (K_E^j)^{\rho_j} + (1-\theta_j)(K_S^j)^{\rho_j}\right)^{1/\rho_j}, \qquad \rho_j \equiv \frac{\sigma_j - 1}{\sigma_j},$$

where $\sigma_j > 0$ is the elasticity of substitution and $\theta_j \in (0,1)$. Then, the output technology and R&D evolution can be expressed as

$$Y(t) = A(t)\, Q_Y(t)^{\alpha_Y} L_u(t)^{1-\alpha_Y}, \qquad \alpha_Y \in (0,1),$$

and

$$\dot{A}(t) = \kappa A(t)^{\phi} Q_R(t)^{\alpha_R} L_s(t)^{1-\alpha_R}, \qquad \alpha_R \in (0,1),\ \kappa > 0,\ \phi < 1.$$

Then, g_A under the general case can be expressed as a conditional growth-rate representation indexed by x (see Appendix D for detailed derivation):

$$g_A = \frac{(1-\alpha_Y)n + \alpha_R \gamma_E - \alpha_R \Omega(x)\,(\gamma_E - \gamma_S)}{(1-\phi)(1-\alpha_Y) - \alpha_R}. \tag{23}$$

where

$$\Omega(x) = \alpha_Y \left(1 - \frac{1}{1 + \frac{1-\theta_Y}{\theta_Y} x^{\sigma_Y - 1}}\right) + (1-\alpha_Y)\left(1 - \frac{1}{1 + \frac{1-\theta_R}{\theta_R} x^{\sigma_R - 1}}\right). \tag{24}$$

where $x \equiv u_E/u_S$ denotes the relative user cost of equipment to structures. Since $u_k = P_k(r + \delta_k + \gamma_k)$, we have

$$x = \frac{u_E}{u_S} = \frac{P_E}{P_S} \cdot \frac{r + \delta_E + \gamma_E}{r + \delta_S + \gamma_S}.$$

Finally, We can define $\omega_{\text{drag}}(x) = \alpha_R \Omega(x)$.

[19] When $\sigma_Y \neq 1$ or $\sigma_R \neq 1$ and $\gamma_E \neq \gamma_S$, the relative user changes over time and constant-growth BGP expressions for (g_A, g_Y) do not apply globally. For this reason, the expressions below are best interpreted as conditional (instantaneous) growth-rate representations.

Special Case: Cobb-Douglas Technology When $\sigma_Y = \sigma_R = 1$ as in benchmark, CES reduces to Cobb-Douglas and the cost shares become constant as follows

$$\alpha_Y = \alpha_E + \alpha_S, \quad \alpha_R = \eta_E + \eta_S, \quad \theta_Y = \frac{\alpha_E}{\alpha_E + \alpha_S}, \quad \theta_R = \frac{\eta_E}{\eta_E + \eta_S}$$

Hence $\Omega(x)$ collapses to

$$\begin{aligned}
\Omega^{CD} &= \alpha_Y(1-\theta_Y) + (1-\alpha_Y)(1-\theta_R) \\
&= (\alpha_E + \alpha_S)\left(1 - \frac{\alpha_E}{\alpha_E + \alpha_S}\right) + \big(1 - \alpha_E - \alpha_S\big)\left(1 - \frac{\eta_E}{\eta_E + \eta_S}\right) \\
&= \alpha_S + \big(1 - \alpha_E - \alpha_S\big)\frac{\eta_S}{\eta_E + \eta_S}.
\end{aligned}$$

and therefore

$$\begin{aligned}
\omega^{CD}_{\text{drag}} \equiv \alpha_R\, \Omega^{CD} &= (\eta_E + \eta_S)\left[\alpha_S + \big(1 - \alpha_E - \alpha_S\big)\frac{\eta_S}{\eta_E + \eta_S}\right] \\
&= (\eta_E + \eta_S)\alpha_S + \big(1 - \alpha_E - \alpha_S\big)\eta_S = \eta_E\alpha_S + \eta_S(1 - \alpha_E) \\
&= \eta_S(1 - \alpha_E) + \eta_E\alpha_S,
\end{aligned}$$

which coincides with equation (17).

Under What Conditions Is Structural Drag Amplified? Relative to the benchmark, the structural drag is amplified if structures take a larger share of the cost of producing capital services, that is, if the equipment cost share falls below its Cobb-Douglas counterpart in the relevant sector.

To make this comparison explicit, define the Cobb-Douglas reference shares θ_Y and θ_R and consider the difference

$$\omega_{\text{drag}}(x) - \omega^{CD}_{\text{drag}} = \alpha_R\alpha_Y\big(\theta_Y - s_{E,Y}(x)\big) + \alpha_R(1-\alpha_Y)\big(\theta_R - s_{E,R}(x)\big). \tag{25}$$

Equation (25) shows that CES in the output sector contributes to amplification through the term $\theta_Y - s_{E,Y}(x)$, while CES in the R&D sector contributes through $\theta_R - s_{E,R}(x)$. The sign of $\theta_j - s_{E,j}(x)$ depends on both σ_j and whether x is above or below one. In the empirically relevant region $x < 1$ (equipment is cheaper than structures, as in our U.S. calibration), we obtain

$$\sigma_j < 1 \Rightarrow s_{E,j}(x) < \theta_j \Rightarrow \text{drag amplification}, \qquad \sigma_j > 1 \Rightarrow s_{E,j}(x) > \theta_j \Rightarrow \text{drag attenuation}.$$

Intuitively, complementarity makes it harder to substitute away from structures when their user cost rises relative to equipment. As a result, structures receive a higher effective weight in unit costs, increasing $\Omega(x)$ and strengthening the negative impact of $(\gamma_E - \gamma_S)$ on the innovation rate. Thus, complementarity between equipment and structures (elasticity below one) strengthens the influence of sluggish structural ISTC on sectoral unit costs and increases the magnitude of the ISTC-gap drag in (23), implying $\omega_{\text{drag}}(x) > \omega_{\text{drag}}^{CD}$ and a strictly larger drag down than in the Cobb-Douglas benchmark.

5 Concluding Remarks

This paper challenges the prevailing view that investment-specific technological change in equipment is a sufficient statistic for understanding long-run growth. By disaggregating capital into equipment and structures, we uncover a fundamental tension in the growth process. While falling equipment prices have indeed lowered the cost of producing output and ideas, rising structures price have simultaneously imposed a binding constraint on capital accumulation and innovation.

Quantitatively, our model since 1970 yields an average per-capita output growth of 1.46 percentage points annually. Of this, ISTC contributes 0.82 percentage points in net terms, reflecting a substantial equipment boost of 1.32 percentage points partially offset by a structural drag of 0.50 percentage points, while the remaining 0.64 percentage points arises from the population component. Of this "structural drag," about three-quarters operates through reduced capital deepening in production, while the remaining quarter reflects the R&D-related structural drag. It is split nearly equally between the direct input channel (raising R&D facility costs) and the indirect resource channel (tightening economy-wide resources for innovation).

These findings carry important implications for growth policy. Efforts to accelerate technological progress in equipment-producing sectors may yield diminishing returns if not accompanied by policies addressing productivity stagnation in the structures sector. Understanding why structures productivity has followed what Goolsbee and Syverson (2023) call a "strange and awful path" remains a critical question for future research. Our framework provides a lens through which to evaluate the aggregate implications of any improvements in construction sector productivity and to assess whether policy interventions targeting the construction sector could meaningfully relax the constraint that structures impose on long-run growth.

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APPENDIX

A Details on Capital Price and Expenditure Measurement

Our primary analysis, which focuses on the role of heterogeneity in capital, utilizes three data sources for measurement: the International Comparison Program (ICP), the Penn World Table (PWT) version 11.0 (especially the "Capital Detail" module), and the National Center for Science and Engineering Statistics (NCSES) Business Enterprise Research and Development (BERD) survey. We rely on the PWT capital detail data mainly to characterize time-series trends in each capital prices, with particular emphasis on equipment and structures. We rely on ICP prices mainly for cross-sectional regressions that relate sectoral price levels to GDP per capita. We use BERD to measure and decompose R&D-related capital expenditures by asset type. This section clarifies what each variable measures and describes its coverage in detail.

A.1 The International Comparison Program (ICP)

We focus on the ICP price measures for two capital categories, Machine and Equipment, `item_1501100`) and structures (structures, `item_1501200`). In the ICP classification, these correspond to the following expenditure items under gross fixed capital formation.

- **Machine and Equipment (`item_1501100`):** This corresponds to `1501100 equipment AND EQUIPMENT` under `1501000 GROSS FIXED CAPITAL FORMATION` in the ICP classification. It covers investment in:
  - `1501110 Metal products and equipment`, (including `1501111 Fabricated metal products, except equipment and equipment`)
  - `1501112 Electrical and optical equipment`
  - `1501115 General purpose equipment`
  - `1501116 Special purpose equipment`
  - `1501120 Transport equipment`
- **Structures (`item_1501200`):** This corresponds to `1501200 structures` under `1501000 GROSS FIXED CAPITAL FORMATION` in the ICP classification. It covers:
  - `1501210 Residential buildings`

- 1501220 Non-residential buildings
- 1501230 Civil engineering works

Other capital formation components in the ICP classification. In addition to 1501100 and 1501200, the ICP capital formation block includes the following components. We report them here for completeness.

- **Other products (**item_1501300**):** 1501300 OTHER PRODUCTS within 1501000 GROSS FIXED CAPITAL FORMATION.
- **Changes in inventories (**item_1502000**):** 1502000 CHANGES IN INVENTORIES within 1500000 GROSS CAPITAL FORMATION.
- **Acquisitions less disposals of valuables (**item_1503000**):** 1503000 ACQUISITIONS LESS DISPOSALS OF VALUABLES within 1500000 GROSS CAPITAL FORMATION.

A.2 Penn World Table (PWT) Capital Detail

PWT capital measures (for example, capital services and relative prices of capital) are constructed from investment data by asset.[20] Because investment is originally estimated at a more disaggregated level, the PWT capital detail file provides a convenient aggregation into four asset groups: *machine and equipment*, *structures*, *transport equipment*, and *other assets*.

- **Machine and Equipment:** including computers, communication equipment, and other equipment.
- **Structures:** including residential and non-residential structures.
- **Transport equipment:** including transport equipment reported as a separate asset group.
- **Other assets:** including software, other intellectual property products, and cultivated assets.

[20] https://www.rug.nl/ggdc/docs/user_guide_to_pwt90_data_files.pdf

A.3 NCSES Business Enterprise Research and Development (BERD): Capital Expenditures Classification

We utilize the National Center for Science and Engineering Statistics (NCSES) Business Enterprise Research and Development (BERD) survey to calibrate the model.

BERD defines capital expenditures as payments for assets that typically have a useful life of more than one year and are recorded on a company's balance sheet. Long-lived assets used in R&D operations are not counted as current R&D expense; instead, any depreciation recorded for those assets would be included in R&D expense.[21]

For the BERD survey year 2015 instrument, the relevant items request *domestic* capital expenditures for R&D operations (Question 2.32) and a required breakdown of those domestic R&D capital expenditures into

- **Structures**: Include the costs of purchased or improved buildings and other facilities such as signal towers or windmills that are fixed to the land
- **Equipment**
- **Capitalized software**
- **All other expenditures**: Include the costs of purchased patents or other intangible assets

in Question 2.33.[22] The instrument also notes that assets acquired through merger and acquisition activities should be excluded, and that capital expenditures benefiting both R&D and non-R&D operations should be allocated on a reasonable basis.

A.4 U.S. Bureau of Economic Analysis (BEA) Fixed Assets and Industry Accounts

For the U.S. focused analyses in the main text, we use detailed data from the U.S. BEA, particularly for the analyses underlying Facts 4. We rely on two main BEA data systems: the Fixed Assets Accounts and the GDP-by-Industry Accounts. Together, these sources allow us to measure asset specific investment prices, capital stocks, industry level exposure to structures, the outcomes.

[21] https://ncses.nsf.gov/surveys/business-enterprise-research-development
[22] https://www2.census.gov/programs-surveys/brdis/information/qbyqbrdi.pdf

Asset Categories. The BEA asset classification[23] allows us to distinguish sharply between equipment and equipment and structures. In the analysis, we define:

- **Equipment**[24] This category includes information-processing equipment (computers and peripheral equipment, communication equipment), industrial equipment, transportation equipment, and other equipment assets.
- **Structures**[25] This category includes residential and nonresidential structures (and associated nonbuilding structures). Importantly, the post-1990 increase in relative structures price documented in the main text is broad based across these subcategories rather than driven by a single component.

BEA Fixed Assets Accounts Based on the above defintion, the BEA Fixed Assets Accounts provide detailed information on investment flows, capital stocks, and implicit price indices by asset type and by industry. We use both investment-based and stock-based measures to characterize the evolution of relative prices and capital composition.

- **Investment in Private Fixed Assets by Asset Type.** We use National Income and Product Accounts (NIPA) Tables 2.7 and 2.8, which report nominal investment and chain-type quantity indexes for private fixed assets by detailed asset category. For each asset type, we construct an implicit investment price index as the ratio of nominal investment to the corresponding chain-type quantity index.
- **Capital Stock by Asset Type.** To verify that the observed investment price dynamics extend to the capital stock itself, we also use BEA Fixed Assets Tables 3.1ESI (Current-Cost Net Stock of Private Fixed Assets) and 3.1S (Current-Cost Net Stock of Private Structures).

[23] BEA NIPA Handbook, Ch. 6 (Dec 2024 update) defines PFI fixed assets as structures, equipment, and intellectual property products. https://www.bea.gov/resources/methodologies/nipa-handbook/pdf/chapter-06.pdf

[24] BEA's capitalization guidance treats an item as *equipment* if it (1) has a useful life of more than 1 year, (2) is *not* an integral part of a structure and is *not* included in the value of that structure (example: an elevator), and (3) would normally be charged to a capital account in business accounting records.

[25] BEA includes in *structures* the structures of new nonresidential and residential buildings, improvements to buildings, and certain types of equipment (e.g., plumbing and heating systems and elevators) that are considered an integral part of the structure; it also includes nonbuilding structures (e.g., pipelines, railroad tracks, power lines and plants, dams and levees), mobile structures, manufactured homes, well drilling and exploration, mine development, brokers' commissions/ownership transfer costs, and net purchases of existing structures from governments.

BEA Fixed Assets Accounts by Industry. To study cross-industry heterogeneity in exposure to structures, we use BEA Fixed Assets Tables that report investment and capital stocks by industry.

- **Investment by Industry.** Structures intensity at the industry level is measured using BEA Table 3.7ESI (Investment in Private Fixed Assets by Industry) and Table 3.7S (Investment in Private Structures by Industry). For each industry, we compute the structures investment share in 1990 as structures investment divided by total private fixed investment.
- **Capital Stock by Industry.** As an alternative measure of exposure, we compute the structures share in the capital stock using Table 3.1ESI (Current-Cost Net Stock of Private Fixed Assets, Equipment, Software, and Intellectual Property Products by Industry) and Table 3.1S (Current-Cost Net Stock of Private Structures by Industry). This stock-based measure captures longer-run technological and cost exposure beyond contemporaneous investment flows.

BEA GDP-by-Industry Accounts. To evaluate the real economic consequences of differential exposure to structures, we combine the Fixed Assets data with industry-level outcomes from the BEA GDP-by-Industry Accounts.

- **Value Added.** Industry value-added shares are obtained from the BEA GDP-by-Industry accounts and are defined as each industry's nominal value added divided by aggregate private-sector value added.
- **Employment.** Employment shares are computed using BEA data on full-time and part-time employment by industry. An industry's employment share is defined as its employment divided by total private employment.

Industry Coverage. The industry-level analysis focuses on major private-sector industries for which consistent investment, capital stock, value added, and employment data are available over time. These include agriculture, mining, utilities, structures, manufacturing (with detailed subsectors), wholesale and retail trade, transportation and warehousing, information, and selected service industries. Excluding a small number of service sectors with limited fixed-asset exposure does not affect the qualitative results.

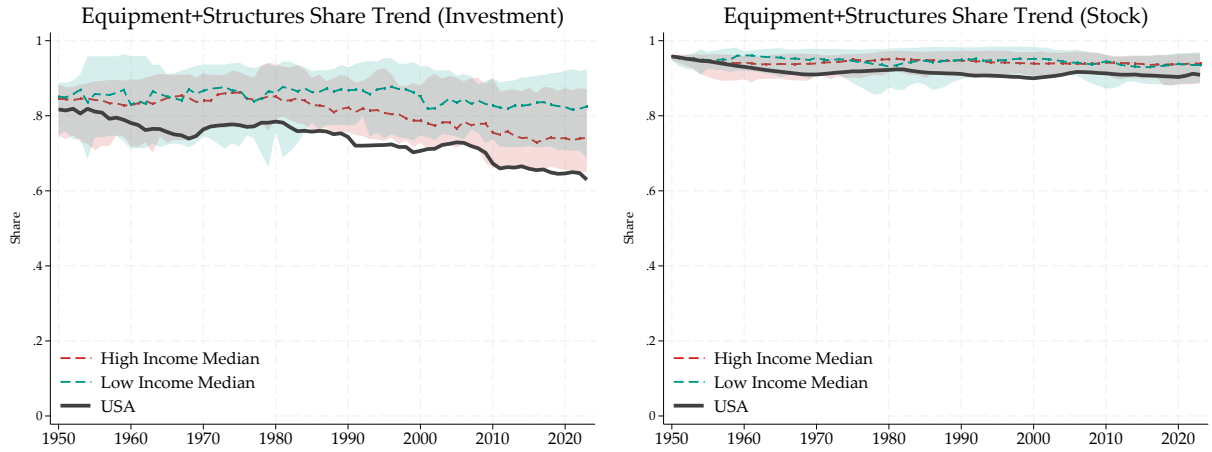
B Robustness Checks on Stylized Facts

B.1 Additional Trends on Fact 1

B.1.1 Investment Share Trend

The components we emphasize in the main text, which are equipment and structures, constitute a large and stable fraction of aggregate investment and capital. Figure B.1 shows that the combined equipment and structures share is high and broadly stable over time in both flows and stocks.

Figure B.1: **Shares of Structure and Equipment in Total Investment**



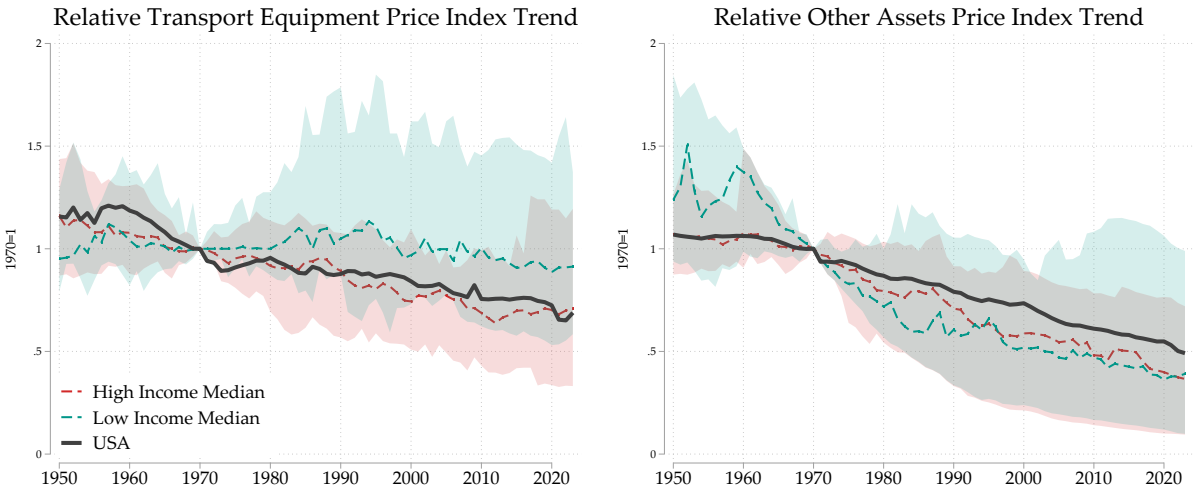
Notes: The figure plots time series of investment shares constructed from Penn World Table capital-detail categories. The share is computed as the ratio of a component to the sum of four components: Structure, Equipment, Transport Equipment, and Other assets. The left panel is based on investment (*Ic*) and the right panel is measured based on captial stock (*Nc*). High and low income groups are defined based on the top and bottom terciles of real GDP per capita in 1970. A total of 120 countries with reported prices in 1970 are included in the analysis. The low-income group (indicated in green) and the high-income group (indicated in red) represent the bottom and top terciles, respectively. Shaded areas represent the 15th to 85th percentile range. Dashed lines indicate the median for each group, and the solid black line denotes the United States as a benchmark. Dashed lines indicate the median for each group, and the solid black line denotes the United States. *Sources:* Penn World Table 11.0; PWT Capital Detail; and authors' calculations.

In the left panel (investment), the group medians remain in a relatively narrow band throughout the sample, indicating that cross-country differences in the evolution of disaggregated relative prices documented in the main text are not driven by large shifts in compositional weights between equipment and structures. In the right panel (capital stock), the combined share is even more stable, with medians close to unity and limited dispersion across groups, consistent with equipment and structures accounting for the overwhelming majority of the capital stock over time.

B.1.2 Relative Price Trend of Other Capital Sectors

PWT's equipment measure does not include transport capital, whereas the ICP data indicate that transport equipment is at least partially incorporated. In addition, the category of other assets may also be subject to compositional mixing. Motivated by these concerns, we replicate the same exercise using price data for transport equipment and other assets.

Figure B.2: **Relative Investment Price Index Trend of Other Capitals**



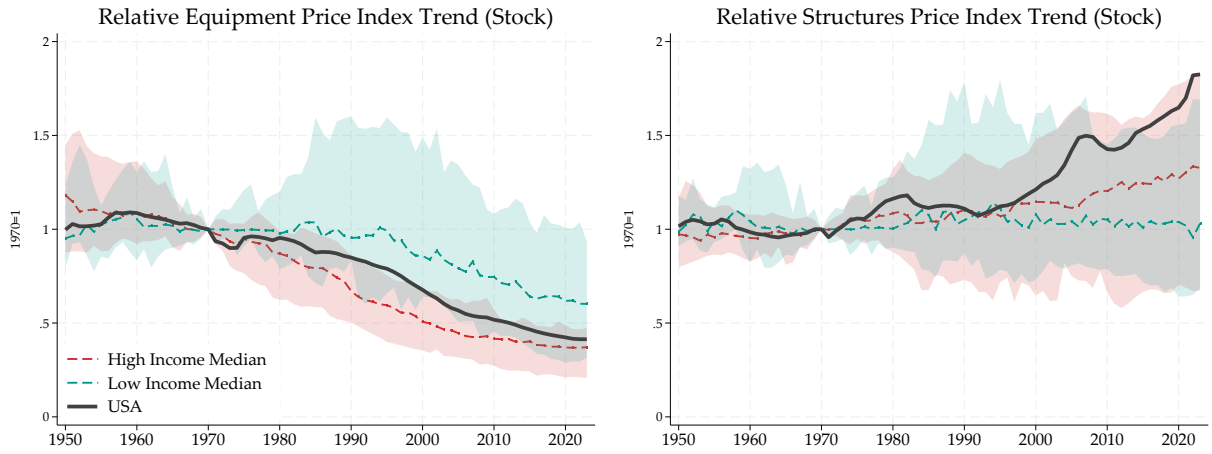
Notes: The relative price for each sector is calculated by dividing each sector's investment price index by the GDP price index, normalized to 1 in 1970. High and low income groups are defined based on the top and bottom terciles of real GDP per capita in 1970. A total of 120 countries with reported prices in 1970 are included in the analysis. The low-income group (indicated in green) and the high-income group (indicated in red) represent the bottom and top terciles, respectively. Shaded areas represent the 15th to 85th percentile range. Dashed lines indicate the median for each group, and the solid black line denotes the United States as a benchmark. Dashed lines indicate the median for each group, and the solid black line denotes the United States. *Sources:* Penn World Table 11.0; PWT Capital Detail; and authors' calculations.

Figure B.2 shows that for these two capital categories it is difficult to identify heterogeneity across the United States, the high-income group, and the low-income group that is as pronounced as what we observe for equipment or structures. This finding mitigates our concern that the cross-group patterns documented for equipment and structures are driven mechanically by category definitions or compositional mixing in the underlying price data. If the inclusion of transport equipment in ICP's equipment, or the potential mixture embedded in other assets, were a first-order source of the observed heterogeneity, we would expect to see similarly large and systematic differences across income groups for transport equipment and other assets themselves. Instead, the absence of comparable divergence suggests that our main results for equipment and structures are unlikely to be an artifact of these classification issues.

B.1.3 Relative Price Trend based on Stock

PWT provides price indices for capital based on capital stocks (Capital Stock Price Indices; series codes begin with `Np`). The stylized facts we report for other capital-asset trends remain unchanged when we use these stock-based price indices. Figure B.3 shows that equipment prices decline more rapidly in high-income economies, including the United States, than in low-income economies. By contrast, for structures, the capital stock price index rises in high-income economies, especially the United States, while it remains relatively stable in low-income economies. The other assets, transport equipment and other asset, show the same pattern found in the previous Appendix, as in Figure B.4.

Figure B.3: **Relative Capital Stock Price Index Trend**



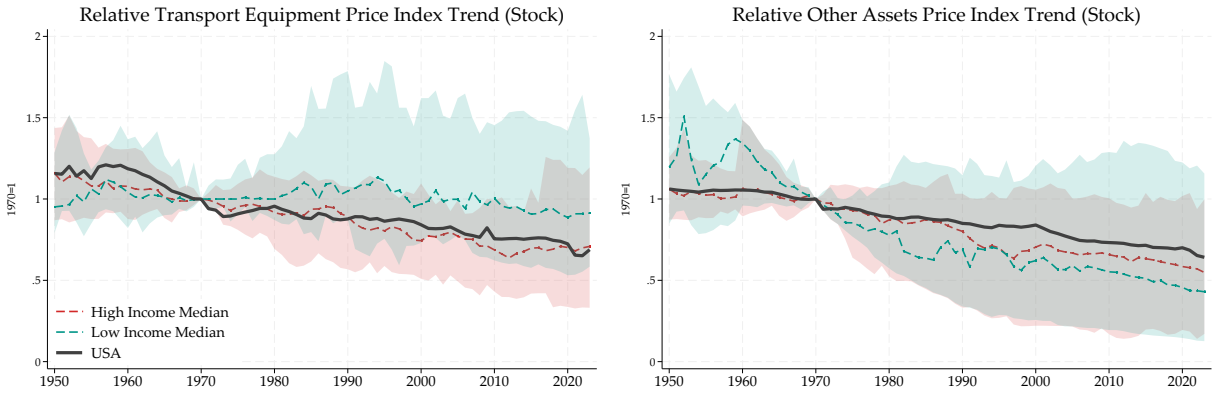
Notes: The relative price for each sector is calculated by dividing each sector's capital stock price index by the GDP price index, normalized to 1 in 1970. High and low income groups are defined based on the top and bottom terciles of real GDP per capita in 1970. A total of 120 countries with reported prices in 1970 are included in the analysis. The low-income group (indicated in green) and the high-income group (indicated in red) represent the bottom and top terciles, respectively. Shaded areas represent the 15th to 85th percentile range. Dashed lines indicate the median for each group, and the solid black line denotes the United States as a benchmark. Dashed lines indicate the median for each group, and the solid black line denotes the United States. *Sources:* Penn World Table 11.0; PWT Capital Detail; and authors' calculations.

B.1.4 Price Trends from ICP

We construct ICP-based cross-country relative prices and how we estimate the evolving cross-sectional relationship between relative prices and income across ICP survey years, and it reports the corresponding figures (Hsieh and Klenow, 2007).

We use ICP survey-year data on PPP prices for (i) equipment, (ii) structures, and (iii) GDP, together with the associated market exchange rate information to express PPP price measures in a common currency basis. We restrict the sample to countries with non-missing information for the relevant items in each survey year and drop aggregate re-

Figure B.4: **Relative Capital Stock Price Index Trend of Other Capitals**



Notes: The relative price for each sector is calculated by dividing each sector's capital stock price index by the GDP price index, normalized to 1 in 1970. High and low income groups are defined based on the top and bottom terciles of real GDP per capita in 1970. A total of 120 countries with reported prices in 1970 are included in the analysis. The low-income group (indicated in green) and the high-income group (indicated in red) represent the bottom and top terciles, respectively. Shaded areas represent the 15th to 85th percentile range. Dashed lines indicate the median for each group, and the solid black line denotes the United States as a benchmark. Dashed lines indicate the median for each group, and the solid black line denotes the United States. *Sources:* Penn World Table 11.0; PWT Capital Detail; and authors' calculations.

gions and non-sovereign groupings. We focus on the ICP benchmark years 1996, 2005, 2011, 2017, and 2021 for consistent cross-year comparisons. Following Hsieh and Klenow (2007), we normalize each variable by the United States within each survey year to facilitate cross-country comparisons. Let $P^k_{i,t}$ denote the PPP price of item $k \in \{\text{equipment, structures}\}$ for country i in survey year t, and let $y_{i,t}$ denote PPP GDP per capita. We construct U.S.-normalized relative prices and income as

$$\tilde{P}^k_{i,t} = \ln\left(\frac{P^k_{i,t}}{P^k_{\text{USA},t}}\right), \qquad \tilde{y}_{i,t} = \ln\left(\frac{y_{i,t}}{y_{\text{USA},t}}\right).$$

For visualization, we plot these ln-based variables on axes labeled in base-2 log units (so that a value of 1 corresponds to twice the U.S. level). The underlying variables remain in natural logs; only the axis scaling and tick labels use base-2 units to aid interpretation. The resulting scatter plots report $\tilde{P}^k_{i,t}$ on the vertical axis and $\tilde{y}_{i,t}$ on the horizontal axis, both normalized to zero for the United States. In addition, for each survey year t, we estimate the income gradient of each relative price using a no-intercept specification:

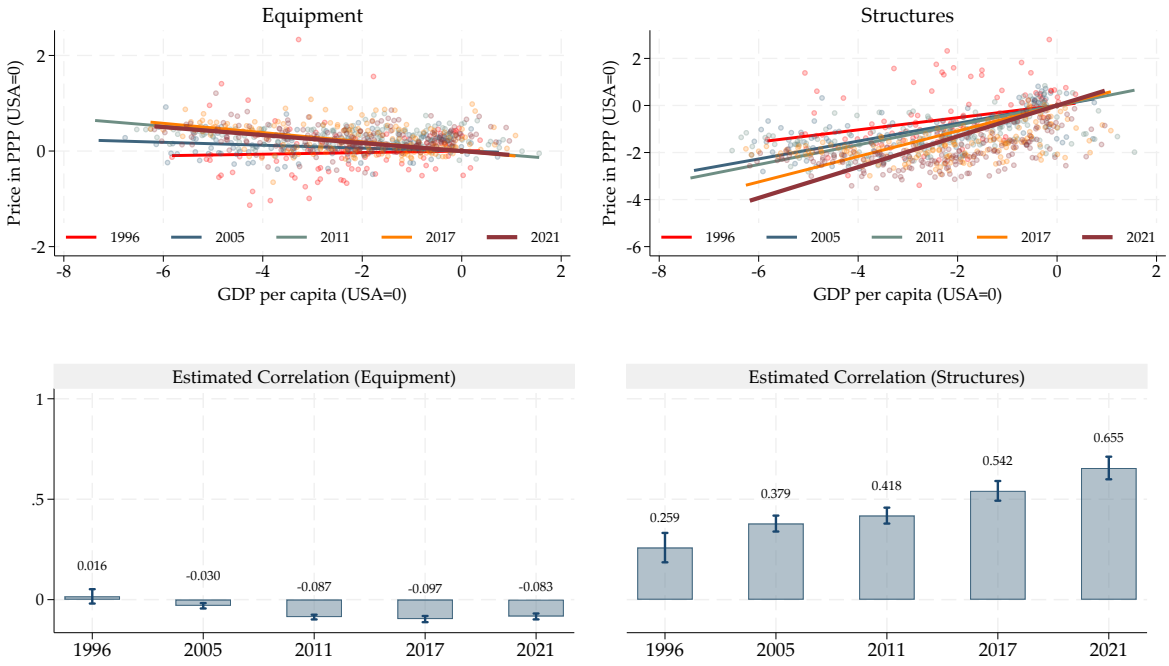
$$\tilde{P}^k_{i,t} = \beta^k_t \, \tilde{y}_{i,t} + \varepsilon^k_{i,t},$$

where β^k_t captures how relative prices covary with relative income in year t.

Figure B.5 presents ICP-based cross-country evidence on relative prices and their income gradients for equipment and structures across survey years (Hsieh and Klenow,

2007). The top row plots, for each ICP benchmark year (1996, 2005, 2011, 2017, and 2021), the cross-country relationship between U.S.-normalized PPP prices and U.S.-normalized PPP GDP per capita. The fitted lines for equipment are relatively stable across years, although the correlation with GDP per capita turns negative over time, whereas the fitted lines for structures become increasingly steep, indicating a strengthening cross-sectional association between structures price and income in later survey waves. The bottom row summarizes the corresponding year-by-year regression slopes and their 95% confidence intervals.

Figure B.5: **ICP cross-country relative prices and income gradients by survey year**



Notes: Each dot is a country. The horizontal axis reports log relative GDP per capita (PPP), normalized so that the United States equals zero in each survey year. The vertical axis reports the corresponding log relative PPP price (equipment or structures), also normalized so that the United States equals zero. The fitted lines in the top row are survey-year specific cross-sectional regressions with no intercept. The bottom row reports the estimated slopes and 95% confidence intervals for equipment and structures by survey year.

B.2 Additional Results on Fact 3

B.2.1 Results on GDP per capita

In our baseline estimation, we controlled for initial conditions using a fixed lagged income term (e.g., $y_{i,t-6}$). While this approach standardizes the control variable across specifica-

tions, it implies that the time horizon between the outcome variable $y_{i,t+h}$ and the control variable varies with the forecast horizon h. To ensure that our results are not driven by these varying lag lengths, we re-estimate the local projections by imposing a constant time gap, denoted by τ, between the dependent variable and the lagged control.

$$\ln(y_{i,t+h}) = \beta^{h,\tau}_{\text{Equip}} \ln(P^{\text{Equip}}_{it}) + \beta^{h,\tau}_{\text{Str}} \ln(P^{\text{Str}}_{it}) + \mathbf{X}'_{it}\Gamma^{h,\tau} + \lambda^{h,\tau} \ln(y_{i,t+h-\tau}) + \alpha^{h,\tau}_i + \delta^{h,\tau}_t + \epsilon^h_{it} \quad \text{(B.1)}$$

Table B.I: **The Effect of Capital Prices on GDP per Capita (Stable Lag Distance)**

	Control Lag Gap (τ = 10)			Control Lag Gap (τ = 6)		
	$\ln(y_{i,t-5})$ (1)	$\ln(y_{i,t})$ (2)	$\ln(y_{i,t+5})$ (3)	$\ln(y_{i,t-5})$ (4)	$\ln(y_{i,t})$ (5)	$\ln(y_{i,t+5})$ (6)
Relative prices						
Log Equipment Price	-0.157*	-0.145	-0.214*	-0.203**	-0.279***	-0.047
	(0.092)	(0.107)	(0.112)	(0.081)	(0.097)	(0.092)
Log structures price	-0.048	-0.156***	0.024	-0.017	-0.064	0.040
	(0.042)	(0.059)	(0.061)	(0.039)	(0.048)	(0.047)
Controls						
Years of Schooling	0.498**	0.266	0.462*	0.419**	0.310*	0.160
	(0.215)	(0.208)	(0.242)	(0.177)	(0.165)	(0.231)
Human Capital Index	-2.118**	-0.779	-2.187*	-1.838**	-1.448*	-0.869
	(1.024)	(0.950)	(1.203)	(0.807)	(0.773)	(1.162)
Log Population	-0.005	0.179	-0.175	0.108	-0.120	-0.163
	(0.140)	(0.142)	(0.134)	(0.099)	(0.113)	(0.100)
Lagged Dependent Variables						
Lagged GDP ($t-15$)	0.018					
	(0.054)					
Lagged GDP ($t-10$)		0.108				
		(0.086)				
Lagged GDP ($t-5$)			0.101			
			(0.072)			
Lagged GDP ($t-11$)				0.458***		
				(0.054)		
Lagged GDP ($t-6$)					0.386***	
					(0.048)	
Lagged GDP ($t-1$)						0.477***
						(0.071)
Constant	-2.121*	-3.780***	-0.717	-0.818	-0.595	-0.350
	(1.092)	(0.943)	(1.286)	(0.763)	(0.828)	(1.088)
Observations	617	617	494	617	632	494
R^2	0.972	0.966	0.969	0.978	0.973	0.974
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors are reported in parentheses and are clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is Log GDP per capita (ln y). Columns (1)–(3) control for lagged GDP per capita with a 10-year gap (τ = 10), while columns (4)–(6) control for lagged GDP per capita with a 6-year gap (τ = 6).

Table B.I presents the estimation results. Columns (1)-(3) utilize a 10-year gap (τ = 10), while Columns (4)-(6) utilize a 6-year gap (τ = 6). The results confirm the dynamic asymmetry observed in the baseline model. The coefficient on equipment prices is negative across horizons, but statistical significance varies across specifications. While the point

estimates for current and future income remain negative in this specification, there is a strong correlation with the past GDP per capita and the equipment prices.

B.2.2 Smoothed Data using Centered Moving Averages

In this section, we check the robustness of our results by replacing the point-in-time outcomes with smoothed measures based on centered moving averages. Specifically, for each selected benchmark year t, we construct the variables as the five-year centered average:

$$\bar{X}_{it} = \frac{X_{i,t-2} + X_{i,t-1} + X_{i,t} + X_{i,t+1} + X_{i,t+2}}{5}$$

This procedure mitigates measurement error and short-run fluctuations. We utilize data from the ICP benchmark years (1990, 1996, 2005, 2011, 2017, 2021) to construct these averages.

Table B.II presents the baseline relationship between relative price and investment rates. Table B.III reports the dynamic specifications for GDP per capita.

Table B.II: **Effect of Relative Prices on Investment Rates (Smoothed Data)**

	Log Equipment Inv. Rate (1)	Log Str. Inv. Rate (2)
Log Equipment Price	-0.714***	0.700***
	(0.272)	(0.212)
Log Structures price	0.143	-0.714***
	(0.094)	(0.080)
Years of Schooling	0.734*	0.456
	(0.430)	(0.382)
Human Capital	-3.389*	-2.388
	(1.969)	(1.769)
Log Population	-0.488	0.249
	(0.437)	(0.295)
Lagged Dep. Var.	-0.028	-0.136
	(0.157)	(0.195)
Constant	0.665	-1.351
	(2.287)	(1.602)
Observations	534	534
R^2	0.724	0.682

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Note on Lags/Forwards: All variables are constructed using 5-year centered moving averages.

Table B.III: **Dynamic Effects on GDP per Capita (Smoothed Data)**

	Specification A (No Lag Control)			Specification B (With Lag Control)		
	Past $L.\ln(y)$ (1)	Current $\ln(y)$ (2)	Future $F.\ln(y)$ (3)	Past $L.\ln(y)$ (4)	Current $\ln(y)$ (5)	Future $F.\ln(y)$ (6)
Log Equipment Price	-0.147*	-0.292***	-0.231**	-0.027	-0.209***	0.002
	(0.081)	(0.100)	(0.106)	(0.078)	(0.078)	(0.081)
Log Structures price	-0.082**	-0.076	0.035	0.048	-0.029	0.051
	(0.036)	(0.047)	(0.059)	(0.035)	(0.037)	(0.041)
Years of Schooling	0.536***	0.559***	0.548**	0.323***	0.256*	0.166
	(0.195)	(0.210)	(0.265)	(0.160)	(0.139)	(0.240)
Human Capital	-2.264**	-2.458**	-2.550*	-1.516***	-1.181*	-0.922
	(0.935)	(0.993)	(1.323)	(0.740)	(0.642)	(1.222)
Log Population	-0.046	-0.114	-0.168	-0.176	-0.088	-0.174**
	(0.114)	(0.132)	(0.134)	(0.126)	(0.096)	(0.084)
Lagged Dep. Var.	No	No	No	Yes ($L2$)	Yes (L)	Yes (F)
Observations	632	632	494	537	632	494
R^2	0.973	0.973	0.972	0.988	0.982	0.980

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Note on Lags/Forwards: Since the data is constructed using benchmark years, one unit of lag ($L.$) or forward ($F.$) corresponds to the adjacent 5-year centered average period. For example, in Column (4), the dependent variable is the previous period's income, and we control for the income two periods prior ($L2.$).

B.2.3 Results on TFP Dynamics

We further investigate whether the observed relative price effects on GDP per capita are driven by productivity channels. To test this mechanism, we estimate the same dynamic panel specification as Equation (B.2), but we replace the dependent variable (and its corresponding lag) with Total Factor Productivity (TFP), denoted as $A_{i,t}$.

$$\ln(A_{i,t+h}) = \beta^{h,\tau}_{\text{Equip}} \ln(P^{\text{Equip}}_{it}) + \beta^{h,\tau}_{\text{Str}} \ln(P^{\text{Str}}_{it}) + \mathbf{X}'_{it}\Gamma^{h,\tau} + \lambda^{h,\tau} \ln(A_{i,t+h-\tau}) + \alpha^{h,\tau}_i + \delta^{h,\tau}_t + \epsilon^h_{it} \quad \text{(B.2)}$$

Table B.IV reports the TFP results under the stable-lag specification. The estimates of β_{Equip} are negative and statistically significant in several columns (e.g., Columns 2, 4, and 5), while the future-TFP estimate with $\tau = 6$ is not statistically significant (Column 6).

Table B.V reports the estimated elasticities of TFP with respect to capital prices across different time horizons using the baseline horizon specification employed in the main GDP per capita analysis. These results broadly mirror the patterns found for aggregate output, reinforcing the specific role of equipment and equipment. First, the results confirm that lower equipment prices are significantly associated with higher current TFP. In the concurrent specification (Column 2), the coefficient for equipment prices is nega-

Table B.IV: **The Effect of Capital Prices on Total Factor Productivity (TFP)**

	Control Lag Gap (τ = 10)			Control Lag Gap (τ = 6)		
	$\ln(A_{i,t-5})$ (1)	$\ln(A_{i,t})$ (2)	$\ln(A_{i,t+5})$ (3)	$\ln(A_{i,t-5})$ (4)	$\ln(A_{i,t})$ (5)	$\ln(A_{i,t+5})$ (6)
Relative prices						
Log Equipment Price	-0.102	-0.163**	-0.072	-0.111**	-0.133**	-0.018
	(0.072)	(0.066)	(0.068)	(0.051)	(0.058)	(0.055)
Log Structures price	-0.015	0.085**	-0.019	0.034	0.075**	-0.022
	(0.034)	(0.040)	(0.037)	(0.028)	(0.035)	(0.028)
Controls						
Years of Schooling	0.157	0.066	0.086	0.118	0.018	0.033
	(0.114)	(0.103)	(0.113)	(0.090)	(0.088)	(0.098)
Human Capital Index	-0.604	-0.245	-0.361	-0.442	-0.047	-0.154
	(0.561)	(0.495)	(0.556)	(0.436)	(0.426)	(0.462)
Lagged Dependent Variables						
Lagged TFP ($t-15$)	0.249*					
	(0.135)					
Lagged TFP ($t-10$)		0.194*				
		(0.102)				
Lagged TFP ($t-5$)			-0.031			
			(0.125)			
Lagged TFP ($t-11$)				0.633***		
				(0.115)		
Lagged TFP ($t-6$)					0.339***	
					(0.092)	
Lagged TFP ($t-1$)						0.341***
						(0.111)
Constant	0.770	0.724	0.911	0.459	0.499	0.548
	(0.588)	(0.462)	(0.586)	(0.444)	(0.398)	(0.470)
Observations	507	522	407	522	522	421
R^2	0.801	0.853	0.850	0.857	0.870	0.860
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors are reported in parentheses and are clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is Log TFP ($\ln A$). Columns (1)–(3) control for lagged TFP with a 10-year gap ($\tau = 10$), while columns (4)–(6) control for lagged TFP with a 6-year gap ($\tau = 6$).

tive and statistically significant ($\beta = -0.133$), indicating that a 10% decrease in the relative price of equipment is associated with an approximately 1.3% increase in TFP. Crucially, the placebo test in Column (1) supports a causal interpretation: current equipment prices have a near-zero and statistically insignificant relationship with past TFP ($\beta = -0.008$). This suggests that the correlation is not driven by persistent country characteristics or reverse causality where high-TFP countries simply have historically cheaper capital. Rather, the improvement in efficiency materializes contemporaneously with the access to affordable equipment. Second, the heterogeneity between capital types is even more pronounced for TFP than for GDP. While equipment prices show a consistent negative elasticity (lower prices boost efficiency), structures price exhibit a positive and sig-

Table B.V: **The Effect of Capital Prices on Total Factor Productivity (TFP)**

	Control: Lagged TFP ($t-6$)			Control: Lagged TFP ($t-10$)		
	$\ln(A_{i,t-5})$	$\ln(A_{i,t})$	$\ln(A_{i,t+5})$	$\ln(A_{i,t-5})$	$\ln(A_{i,t})$	$\ln(A_{i,t+5})$
	(1)	(2)	(3)	(4)	(5)	(6)
Relative prices						
Log Equipment Price	-0.008	-0.133**	-0.078	-0.096*	-0.163**	-0.069
	(0.019)	(0.058)	(0.069)	(0.049)	(0.066)	(0.065)
Log Structures price	-0.006	0.075**	-0.019	0.034	0.085**	-0.025
	(0.013)	(0.035)	(0.037)	(0.025)	(0.040)	(0.038)
Controls						
Years of Schooling	-0.035	0.018	0.093	0.110	0.066	0.079
	(0.035)	(0.088)	(0.116)	(0.083)	(0.103)	(0.113)
Human Capital Index	0.150	-0.047	-0.385	-0.451	-0.245	-0.338
	(0.172)	(0.426)	(0.571)	(0.397)	(0.495)	(0.548)
Lagged Log TFP ($t-6$)	1.023***	0.339***	-0.090			
	(0.051)	(0.092)	(0.136)			
Lagged Log TFP ($t-10$)				0.686***	0.194*	-0.083
				(0.132)	(0.102)	(0.076)
Constant	-0.103	0.499	0.956	0.514	0.724	0.941*
	(0.187)	(0.398)	(0.598)	(0.408)	(0.462)	(0.559)
Observations	522	522	407	522	522	407
R^2	0.981	0.870	0.852	0.866	0.853	0.851
Country FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓

Notes: Standard errors are reported in parentheses and are clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. The dependent variable is log TFP at different time horizons ($t-5, t, t+5$).

nificant relationship with TFP in the concurrent specification ($\beta = 0.075$). This contrast underscores that while structures are a consequence of development, affordable equipment is a driver of productive efficiency (Jones, 1994).

Finally, Table B.VI shows robust results under smoothed data.

B.3 Additional results on Fact 4

We conduct a parallel exercise using BEA data on current-cost net capital stocks in order to assess whether the patterns observed for investment prices extend to capital stock prices. Figure B.6 plots relative net capital stock price indices by BEA asset type over the period 1960–2020. The structures closely mirror that of the investment price indices: for each asset category, an implicit stock price index is recovered from nominal net capital stock values divided by the corresponding chain-type quantity indices, deflated by the CPI, and normalized to unity in 1970.

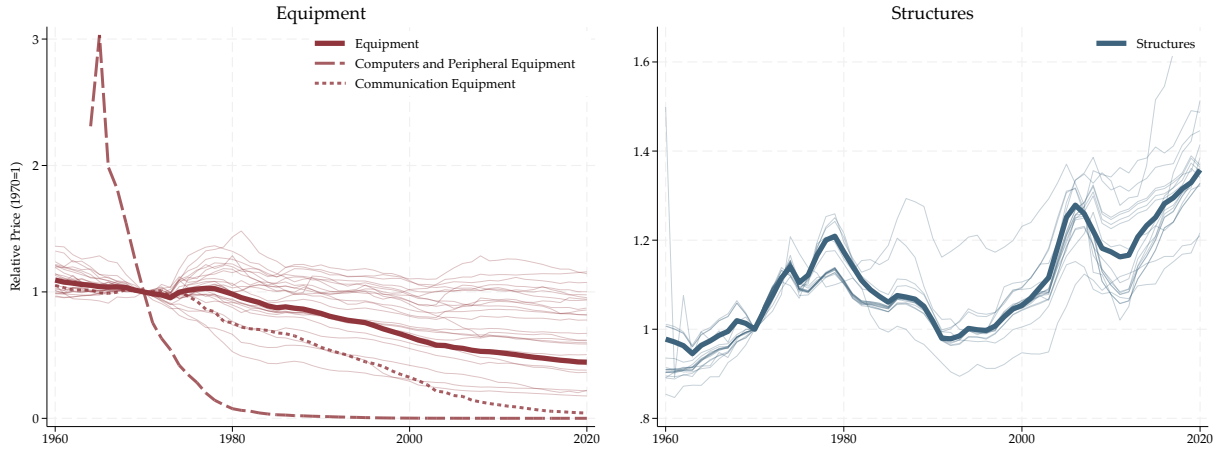
The resulting trends closely mirror those for investment prices. Equipment prices fall sharply after 1970, driven primarily by information-processing assets such as comput-

Table B.VI: **Dynamic Effects on TFP (Smoothed Data)**

	Past *L*.TFP (1)	Current TFP (2)	Future *F*.TFP (3)
Log Equipment Price	-0.104	-0.169**	-0.081
	(0.075)	(0.070)	(0.067)
Log Structures price	-0.007	0.088**	0.008
	(0.031)	(0.040)	(0.039)
Years of Schooling	0.142	0.078	0.137
	(0.140)	(0.114)	(0.121)
Human Capital	-0.635	-0.324	-0.605
	(0.676)	(0.548)	(0.592)
Log Population	0.092	0.063	-0.075
	(0.130)	(0.079)	(0.092)
Constant	0.935	0.807	1.299*
	(0.841)	(0.606)	(0.708)
Observations	522	536	421
R^2	0.800	0.843	0.816

Notes: Standard errors in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Note on Lags/Forwards: All variables are 5-year centered moving averages. One unit of lag (*L*.) or forward (*F*.) corresponds to the previous or next 5-year average period.

Figure B.6: **Relative Net Stock Price Index Trend by Sector (1950-2020)**



Notes: The figure plots trends in relative net capital stock prices by BEA asset type. For each category, we construct an implicit net-stock price index as nominal current-cost net capital stock divided by the corresponding chain-type quantity index for net stocks. The resulting series is deflated by the Consumer Price Index (CPI) and normalized to 1 in 1970 for each category. The sample is restricted to 1960–2020. Thin lines show disaggregated categories, while thicker highlighted lines emphasize the aggregate equipment series and selected subcomponents (computers and peripheral equipment, and communication equipment). *Sources:* U.S. Bureau of Economic Analysis (BEA), BEA Fixed Assets Tables 3.1ESI and 3.1S; Federal Reserve Bank of St. Louis (FRED), CPI for All Urban Consumers: All Items (CPIAUCSL); and authors' calculations.

ers and peripheral equipment and communication equipment, while structures price rise broadly after 1990 across disaggregated categories. Overall, the close alignment between investment- and stock-price trends suggests that these divergent dynamics are not unique

to investment flows but are also reflected in the evolution of the capital stock itself.

C Detailed Derivations of the Balanced Growth Path

In this appendix, we provide a step-by-step derivation of the BGP equilibrium when both equipment and structures are used as inputs in R&D. We define the BGP as a trajectory where aggregate variables $(Y, C, I_E, I_S, K_E, K_S)$ grow at constant rates and sectoral allocations (e.g., K_E^Y/K_E, K_S^Y/K_S, K_E^R/K_E, K_S^R/K_S) remain constant over time.

Step 1: Capital Accumulation and Capital Growth Rates

The laws of motion are

$$\dot{K}_E(t) = q_E(t)I_E(t) - \delta_E K_E(t), \tag{C.1}$$

$$\dot{K}_S(t) = q_S(t)I_S(t) - \delta_S K_S(t), \tag{C.2}$$

with exogenous ISTC growth

$$\frac{\dot{q}_E(t)}{q_E(t)} = \gamma_E, \qquad \frac{\dot{q}_S(t)}{q_S(t)} = \gamma_S.$$

Dividing by stocks,

$$g_{K_E}(t) \equiv \frac{\dot{K}_E(t)}{K_E(t)} = \frac{q_E(t)I_E(t)}{K_E(t)} - \delta_E, \tag{C.3}$$

$$g_{K_S}(t) \equiv \frac{\dot{K}_S(t)}{K_S(t)} = \frac{q_S(t)I_S(t)}{K_S(t)} - \delta_S. \tag{C.4}$$

On a BGP, g_{K_E} and g_{K_S} are constant. With constant investment shares, $g_{I_E} = g_{I_S} = g_Y$. Hence the ratio $\frac{q_k I_k}{K_k}$ must be constant, implying

$$g_{q_k} + g_{I_k} = g_{K_k}, \qquad k \in \{M, C\}.$$

Using $g_{q_E} = \gamma_E$ and $g_{q_S} = \gamma_S$ yields

$$g_{K_E} = g_Y + \gamma_E, \tag{C.5}$$

$$g_{K_S} = g_Y + \gamma_S. \tag{C.6}$$

Step 2: Final-Goods Production and the g_Y–g_A Relationship

The final-goods technology is

$$Y(t) = A(t)\big(K_E^Y(t)\big)^{\alpha_E}\big(K_S^Y(t)\big)^{\alpha_S}\big(L_u(t)\big)^{1-\alpha_E-\alpha_S}.$$

Taking logs and differentiating,

$$g_Y = g_A + \alpha_E g_{K_E^Y} + \alpha_S g_{K_S^Y} + (1-\alpha_E-\alpha_S)n.$$

On the BGP, the sectoral allocation shares are constant, so $g_{K_E^Y} = g_{K_E}$ and $g_{K_S^Y} = g_{K_S}$. Substituting (C.5)–(C.6),

$$g_Y = g_A + \alpha_E(g_Y + \gamma_E) + \alpha_S(g_Y + \gamma_S) + (1-\alpha_E-\alpha_S)n.$$

Collecting g_Y terms,

$$(1-\alpha_E-\alpha_S)g_Y = g_A + \alpha_E\gamma_E + \alpha_S\gamma_S + (1-\alpha_E-\alpha_S)n,$$

so

$$g_Y = \frac{g_A}{1-\alpha_E-\alpha_S} + \frac{\alpha_E\gamma_E + \alpha_S\gamma_S}{1-\alpha_E-\alpha_S} + n. \tag{C.7}$$

Step 3: Innovation Production and the Second Relationship

R&D produces new designs according to

$$\dot{A}(t) = \kappa A(t)^{\phi}\big(K_E^R(t)\big)^{\eta_E}\big(K_S^R(t)\big)^{\eta_S}\big(L_s(t)\big)^{1-\eta_E-\eta_S}.$$

Dividing by $A(t)$,

$$g_A \equiv \frac{\dot{A}(t)}{A(t)} = \kappa A(t)^{\phi-1}\big(K_E^R(t)\big)^{\eta_E}\big(K_S^R(t)\big)^{\eta_S}\big(L_s(t)\big)^{1-\eta_E-\eta_S}.$$

For g_A to be constant on the BGP, the growth rate of the RHS must be zero:

$$0 = (\phi-1)g_A + \eta_E g_{K_E^R} + \eta_S g_{K_S^R} + (1-\eta_E-\eta_S)n.$$

Equivalently,

$$(1-\phi)g_A = \eta_E g_{K_E^R} + \eta_S g_{K_S^R} + (1-\eta_E-\eta_S)n. \tag{C.8}$$

On the BGP, $g_{K_E^R} = g_{K_E}$ and $g_{K_S^R} = g_{K_S}$, so using (C.5)–(C.6),

$$(1-\phi)g_A = (\eta_E + \eta_S)g_Y + \eta_E\gamma_E + \eta_S\gamma_S + (1-\eta_E-\eta_S)n. \tag{C.9}$$

Step 4: Solving for (g_A, g_Y)

Let $\boldsymbol{\alpha} \equiv 1-\alpha_E-\alpha_S$ and $\boldsymbol{\eta} \equiv \eta_E+\eta_S$. From (C.7),

$$g_Y = \frac{g_A}{\boldsymbol{\alpha}} + \frac{\alpha_E\gamma_E + \alpha_S\gamma_S}{\boldsymbol{\alpha}} + n.$$

Substitute into (C.9):

$$\begin{aligned}(1-\phi)g_A &= \boldsymbol{\eta}\left[\frac{g_A}{\boldsymbol{\alpha}} + \frac{\alpha_E\gamma_E + \alpha_S\gamma_S}{\boldsymbol{\alpha}} + n\right] + \eta_E\gamma_E + \eta_S\gamma_S + (1-\boldsymbol{\eta})n \\ &= \frac{\boldsymbol{\eta}}{\boldsymbol{\alpha}}g_A + \frac{\boldsymbol{\eta}}{\boldsymbol{\alpha}}(\alpha_E\gamma_E + \alpha_S\gamma_S) + n + \eta_E\gamma_E + \eta_S\gamma_S.\end{aligned}$$

Collecting g_A terms,

$$g_A\left[(1-\phi) - \frac{\boldsymbol{\eta}}{\boldsymbol{\alpha}}\right] = n + \frac{\boldsymbol{\eta}}{\boldsymbol{\alpha}}(\alpha_E\gamma_E + \alpha_S\gamma_S) + \eta_E\gamma_E + \eta_S\gamma_S.$$

Multiplying by $\boldsymbol{\alpha}$,

$$g_A\big[(1-\phi)\boldsymbol{\alpha} - \boldsymbol{\eta}\big] = \boldsymbol{\alpha}n + \boldsymbol{\eta}(\alpha_E\gamma_E + \alpha_S\gamma_S) + \boldsymbol{\alpha}(\eta_E\gamma_E + \eta_S\gamma_S).$$

Therefore,

$$g_A = \frac{\boldsymbol{\alpha}n + \boldsymbol{\eta}(\alpha_E\gamma_E + \alpha_S\gamma_S) + \boldsymbol{\alpha}(\eta_E\gamma_E + \eta_S\gamma_S)}{(1-\phi)\boldsymbol{\alpha} - \boldsymbol{\eta}}. \tag{C.10}$$

An equivalent expanded expression is

$$g_A = \frac{(1-\alpha_E-\alpha_S)n + \big(\eta_E(1-\alpha_S) + \eta_S\alpha_E\big)\gamma_E + \big(\eta_S(1-\alpha_E) + \eta_E\alpha_S\big)\gamma_S}{(1-\phi)(1-\alpha_E-\alpha_S) - (\eta_E+\eta_S)}.$$

Given g_A, output growth follows from (C.7):

$$g_Y = \frac{g_A}{1-\alpha_E-\alpha_S} + \frac{\alpha_E\gamma_E + \alpha_S\gamma_S}{1-\alpha_E-\alpha_S} + n. \tag{C.11}$$

A finite BGP requires $(1-\phi)(1-\alpha_E-\alpha_S) > (\eta_E+\eta_S)$.

C.1 Consistency Checks: Factor Prices

1. Rental rate of equipment in final goods. From $R_E = \alpha_E Y / K_E^Y$,

$$g_{R_E} = g_Y - g_{K_E^Y} = g_Y - (g_Y + \gamma_E) = -\gamma_E.$$

2. Rental rate of structures in final goods. From $R_S = \alpha_S Y / K_S^Y$,

$$g_{R_S} = g_Y - g_{K_S^Y} = g_Y - (g_Y + \gamma_S) = -\gamma_S.$$

3. Unskilled wage. From $w_u = (1 - \alpha_E - \alpha_S) Y / L_u$ with $g_{L_u} = n$,

$$g_{w_u} = g_Y - n.$$

4. Skilled wage and design value. From the R&D FOC,

$$w_s = (1 - \eta_E - \eta_S) \frac{p_A \dot{A}}{L_s}.$$

Since $g_{\dot{A}} = g_A$ on the BGP and $g_{L_s} = n$,

$$g_{w_s} = g_{p_A} + g_A - n.$$

If the wage premium is constant on the BGP (i.e., w_s / w_u constant), then $g_{w_s} = g_{w_u}$, implying

$$g_{p_A} = g_Y - g_A,$$

which is consistent with the shadow-value dynamics in (**??**).

5. Consistency of R&D capital demands (both capitals). From the R&D FOCs,

$$R_E = \eta_E \frac{p_A \dot{A}}{K_E^R}, \qquad R_S = \eta_S \frac{p_A \dot{A}}{K_S^R}.$$

Thus,

$$g_{R_E}^{R\&D} = g_{p_A} + g_A - g_{K_E^R} = (g_Y - g_A) + g_A - (g_Y + \gamma_E) = -\gamma_E,$$
$$g_{R_S}^{R\&D} = g_{p_A} + g_A - g_{K_S^R} = (g_Y - g_A) + g_A - (g_Y + \gamma_S) = -\gamma_S,$$

which matches the growth rates implied by the final-goods sector, so both capital markets clear consistently on the BGP.

C.2 Consistency Checks: Household No-Arbitrage and Interest Rate Consistency

No-arbitrage for each capital type implies

$$r(t) = \frac{R_E(t)}{P_E(t)} + \frac{\dot{P}_E(t)}{P_E(t)} - \delta_E = q_E(t)R_E(t) - \gamma_E - \delta_E,$$
$$r(t) = \frac{R_S(t)}{P_S(t)} + \frac{\dot{P}_S(t)}{P_S(t)} - \delta_S = q_S(t)R_S(t) - \gamma_S - \delta_S.$$

On the BGP, $g_{q_E R_E} = \gamma_E + g_{R_E} = \gamma_E - \gamma_E = 0$ and $g_{q_S R_S} = \gamma_S + g_{R_S} = \gamma_S - \gamma_S = 0$, so $r(t)$ is constant.

Finally, since $C(t)$ grows at rate g_Y on the BGP, per-capita consumption grows at $g_S = g_Y - n$. The Euler equation implies the constant interest rate

$$r = \rho + \sigma(g_Y - n).$$

D Detailed Derivation on CES Extension Case

The key conceptual point is that, under CES aggregation with $\gamma_E \neq \gamma_S$, the relative user cost $x(t)$ typically evolves over time, implying time-varying cost shares and, therefore, the lack of a global constant-growth BGP in general. For that reason, the results below are derived as conditional (instantaneous) growth-rate representations indexed by $x(t)$.

Let $u_E(t)$ and $u_S(t)$ denote the (final-good denominated) user costs of equipment and structures. Under the same no-arbitrage logic used in the main text, a convenient reduced-form representation is

$$u_E(t) = P_E(t)\left(r(t) + \delta_E + \gamma_E\right), \qquad u_S(t) = P_S(t)\left(r(t) + \delta_S + \gamma_S\right).$$

Define the relative user-cost ratio

$$x(t) \equiv \frac{u_E(t)}{u_S(t)}.$$

When $r(t)$ is approximately stationary at low frequency, the trend in $x(t)$ is primarily driven by the differential ISTC component $(\gamma_E - \gamma_S)$ through (P_E/P_S).

In each sector $j \in \{Y, R\}$, define CES capital services

$$Q_j\left(K_E^j, K_S^j\right) = \left(\theta_j (K_E^j)^{\rho_j} + (1-\theta_j)(K_S^j)^{\rho_j}\right)^{1/\rho_j}, \qquad \rho_j \equiv \frac{\sigma_j - 1}{\sigma_j}, \tag{D.1}$$

where $\sigma_j > 0$ is the elasticity of substitution and $\theta_j \in (0,1)$.

Let $c_{Q,j}(u_E, u_S)$ denote the unit cost of producing one unit of Q_j given user costs (u_E, u_S). For the CES aggregator in (D.1), the unit cost is

$$c_{Q,j}(u_E, u_S) = \left(\theta_j u_E^{1-\sigma_j} + (1-\theta_j) u_S^{1-\sigma_j}\right)^{\frac{1}{1-\sigma_j}}, \qquad (\sigma_j \neq 1). \tag{D.2}$$

The Cobb-Douglas case $\sigma_j = 1$ is obtained as the continuous limit: $c_{Q,j}(u_E, u_S) = u_E^{\theta_j} u_S^{1-\theta_j}$.

Let $s_{E,j}$ denote the equipment cost share in sector j for producing Q_j. Shephard's lemma implies

$$s_{E,j}(u_E, u_S) = \frac{\partial \ln c_{Q,j}(u_E, u_S)}{\partial \ln u_E}.$$

Using (D.2), a standard CES algebra delivers

$$s_{E,j}(u_E, u_S) = \frac{\theta_j u_E^{1-\sigma_j}}{\theta_j u_E^{1-\sigma_j} + (1-\theta_j) u_S^{1-\sigma_j}} = \frac{1}{1 + \frac{1-\theta_j}{\theta_j}\left(\frac{u_S}{u_E}\right)^{1-\sigma_j}}. \tag{D.3}$$

Expressed in terms of $x \equiv u_E/u_S$, this becomes

$$s_{E,j}(x) = \frac{1}{1 + \frac{1-\theta_j}{\theta_j} x^{\sigma_j - 1}}. \tag{D.4}$$

The structures share is $1 - s_{E,j}(x)$. Now, log-differentiating $c_{Q,j}$ and using the envelope property yields

$$g_{c_{Q,j}} = s_{E,j}(x)\, g_{u_E} + \big(1 - s_{E,j}(x)\big)\, g_{u_S}. \tag{D.5}$$

With approximately stationary $r(t)$ at low frequency, $g_{u_E} \approx g_{P_E} = -\gamma_E$ and $g_{u_S} \approx g_{P_S} = -\gamma_S$, so

$$g_{c_{Q,j}} \approx -\Big(s_{E,j}(x)\gamma_E + \big(1 - s_{E,j}(x)\big)\gamma_S\Big) = -\gamma_E + \big(1 - s_{E,j}(x)\big)\,(\gamma_E - \gamma_S). \tag{D.6}$$

It is useful to define the effective ISTC term in sector j as the negative of the unit-cost growth:

$$\gamma_{Q,j}(x) \equiv -g_{c_{Q,j}} \approx \gamma_E - \big(1 - s_{E,j}(x)\big)\,(\gamma_E - \gamma_S). \tag{D.7}$$

When structures become more important in the cost of services (lower $s_{E,j}(x)$), the effective ISTC $\gamma_{Q,j}(x)$ falls for a given gap $(\gamma_E - \gamma_S)$.

Now assume the sectoral technologies as in the main text:

$$\begin{aligned} Y(t) &= A(t)\, \boldsymbol{Q}_Y(t)^{\alpha_Y}\, L_u(t)^{1-\alpha_Y}, \\ \dot{A}(t) &= \kappa\, A(t)^{\phi}\, \boldsymbol{Q}_R(t)^{\alpha_R}\, L_s(t)^{1-\alpha_R}, \end{aligned}$$

with $L_u(t) = (1-s)N(t)$, $L_s(t) = sN(t)$, and $\dot{N}(t) = nN(t)$.

Log-differentiating the final-good technology gives

$$g_Y = g_A + \alpha_Y g_{\boldsymbol{Q}_Y} + (1 - \alpha_Y)n. \tag{D.8}$$

From $\dot{A} = \kappa A^{\phi} \boldsymbol{Q}_R^{\alpha_R} L_s^{1-\alpha_R}$,

$$g_A = \kappa A^{\phi-1} \boldsymbol{Q}_R^{\alpha_R} L_s^{1-\alpha_R}. \tag{D.9}$$

Taking logs and differentiating the RHS and imposing constant-growth in the sense of a conditional growth-rate representation yields

$$(1 - \phi) g_A = \alpha_R g_{\boldsymbol{Q}_R} + (1 - \alpha_R)n. \tag{D.10}$$

Under competitive cost minimization, the growth of the capital-services aggregate can be expressed in a way that parallels the Cobb-Douglas case, except that the effective ISTC

depends on x through the unit-cost index. A convenient reduced-form representation that matches the main text is

$$g_{Q_j} = g_Y + \gamma_{Q,j}(x), \qquad j \in \{Y, R\}, \tag{D.11}$$

where $\gamma_{Q,j}(x)$ is the effective ISTC term defined in (D.7). Intuitively, Q_j scales with economy-wide accumulation and is tilted by the sector-specific effective ISTC that depends on the relative user-cost ratio x. Substituting (D.11) into (D.8) gives

$$g_Y = g_A + \alpha_Y\big(g_Y + \gamma_{Q,Y}(x)\big) + (1-\alpha_Y)n. \tag{D.12}$$

hence

$$(1-\alpha_Y)g_Y = g_A + \alpha_Y\gamma_{Q,Y}(x) + (1-\alpha_Y)n, \qquad g_Y = n + \frac{g_A}{1-\alpha_Y} + \frac{\alpha_Y}{1-\alpha_Y}\gamma_{Q,Y}(x). \tag{D.13}$$

Next, substituting (D.11) into (D.10) yields

$$(1-\phi)g_A = \alpha_R\big(g_Y + \gamma_{Q,R}(x)\big) + (1-\alpha_R)n. \tag{D.14}$$

Using (D.13) to eliminate g_Y gives a closed-form conditional expression for g_A.

To match the main-text notation, define

$$\Omega(x) \equiv \alpha_Y\Big(1 - s_{E,Y}(x)\Big) + (1-\alpha_Y)\Big(1 - s_{E,R}(x)\Big), \tag{D.15}$$

with $s_{E,j}(x)$ given by (D.4). This object collects the weights on the structures cost shares across the two sectors. Using (D.7), one can write the effective ISTC terms as

$$\gamma_{Q,Y}(x) = \gamma_E - \big(1 - s_{E,Y}(x)\big)(\gamma_E - \gamma_S), \qquad \gamma_{Q,R}(x) = \gamma_E - \big(1 - s_{E,R}(x)\big)(\gamma_E - \gamma_S).$$

After substitution and simplification, the conditional knowledge-growth representation can be written as

$$g_A = \frac{(1-\alpha_Y)n + \alpha_R\gamma_E - \alpha_R\Omega(x)\,(\gamma_E - \gamma_S)}{(1-\phi)(1-\alpha_Y) - \alpha_R}. \tag{D.16}$$

This matches the main-text structure: the ISTC gap $(\gamma_E - \gamma_S)$ reduces g_A through an x-dependent weight $\alpha_R\Omega(x)$.

Explicit closed form for $\Omega(x)$. Using (D.4),

$$1 - s_{E,j}(x) = 1 - \frac{1}{1 + \frac{1-\theta_j}{\theta_j} x^{\sigma_j - 1}}. \tag{D.17}$$

Substituting (D.17) into (D.15) yields

$$\Omega(x) = \alpha_Y \left(1 - \frac{1}{1 + \frac{1-\theta_Y}{\theta_Y} x^{\sigma_Y - 1}}\right) + (1 - \alpha_Y) \left(1 - \frac{1}{1 + \frac{1-\theta_R}{\theta_R} x^{\sigma_R - 1}}\right), \tag{D.18}$$

which corresponds to the expression reported in the main text.

When $\sigma_Y = \sigma_R = 1$, we have $s_{E,Y}(x) = \theta_Y$ and $s_{E,R}(x) = \theta_R$ for all x. Then (D.15) becomes

$$\Omega^{CD} = \alpha_Y(1 - \theta_Y) + (1 - \alpha_Y)(1 - \theta_R),$$

and therefore $\omega_{\text{drag}}(x) \equiv \alpha_R \Omega(x)$ reduces to the constant Cobb-Douglas weight $\omega_{\text{drag}}^{CD} = \alpha_R \Omega^{CD}$, consistent with the benchmark formula in the main text.

A useful implication follows from (D.4). When $\sigma_j < 1$ (complements), an increase in x reduces the equipment cost share $s_{E,j}(x)$ below its Cobb-Douglas counterpart, raising $1 - s_{E,j}(x)$ and therefore increasing $\Omega(x)$ relative to the Cobb-Douglas benchmark. This enlarges the magnitude of the gap term in (D.16) and amplifies the drag from sluggish structures ISTC. When $\sigma_j > 1$ (substitutes), the opposite mechanism attenuates the drag.