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

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Abstract

The falling relative price of equipment, long viewed as the signature of investment-specific technological change (ISTC), has a countervailing force: rising structures prices. We establish four facts: high-income countries' structures prices rise as equipment prices fall; each investment rate falls with its own price; equipment prices predict income growth more strongly than structures prices; and U.S. structures price rises are broad-based. KLEMS data attribute roughly half the post-1996 rise in construction prices, in the U.S. and abroad, to declining construction TFP. We build a two-capital endogenous growth model with structures in production and R&D. Calibrated to the U.S., structures impose a structural drag of 0.50 percentage points per year, partially offsetting a 1.32 percentage point equipment boost. A nested CES extension finds structures-unskilled substitutability alongside equipment-skilled complementarity. These margins shrink the drag by 20–30% and reveal a novel channel whose omission overstates the 1963–2019 U.S. skill premium rise by 30%.

JEL classification

O30, O40, E22

Keywords

equipment, structures, investment-specific technological change, endogenous growth

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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 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 prices 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 types of capital 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 prices 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 shed light on why the relative price of structures has risen, we decompose construction-sector output prices using KLEMS data. At the aggregate level, TFP growth largely absorbs input-cost pressure. In construction, by contrast, weak TFP amplifies rather than offsets rising costs. From 1996 to 2020, about half of the cumulative increase in the construction sector's relative output price is explained by declining total factor productivity. This pattern extends beyond the United States. We document similar productivity shortfalls in the construction sectors of Japan, the United Kingdom, Germany, and France.

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 equipment 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 quantifies the consequences of ISTC in both 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. The structural drag operates through three channels. The first is reduced capital deepening: when structures prices rise, the steady-state capital–output ratio of structures falls. The second and third channels operate through the R&D sector. Structures enter knowledge production directly as a physical input (laboratory and office space), so their rising relative price raises the user cost of research capital. They also enter indirectly through the aggregate resource constraint: weaker growth in the structures tightens the resources available to fund innovation. The R&D channels explain why the collapsing price of equipment did not, by itself, ignite an explosion in idea production.

We calibrate the model to the U.S. economy. Quantitatively, our model since 1970 yields an average per-capita output growth of 1.46 percentage points annually.[1] 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 using estimates from Garcia and Molloy (2025), who bound the bias from unobserved structure quality; for the aggregate construction sector, this bias ranges from near zero to a generous upper bound of roughly 0.5 percentage points per year, resting on the permissive unobservable-selection assumptions built into the Oster (2019) bounding

[1] The actual annual average growth rate was 1.69%.

method. Even at that upper bound, the correction reduces the baseline structural drag from 0.50 to about 0.25 percentage points, attenuating but not eliminating its quantitative importance.

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 (LIC) economies 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 is driven almost entirely by the severe "structural drag" in the U.S. Of the 0.35 percentage point 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.[2] 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. advantage of 0.10 percentage points in GDP per capita growth rate reflects a 0.56 percentage point equipment advantage that is offset by a 0.46 percentage points larger structural drag.

Beyond Cobb–Douglas, we extend the model to a nested CES specification with an equipment–skilled-labor bundle and a structures–unskilled-labor bundle, and estimate the substitution elasticities by GMM on the dataset of Ohanian et al. (2023). The data reject Cobb–Douglas in both nests. Structures and unskilled labor are substitutes ($\hat{\sigma}_S = 2.239$), and the two input bundles are substitutes in the outer nest ($\hat{\sigma}_0 = 1.418$), while equipment and skilled labor remain complements ($\hat{\sigma}_M = 0.716$), preserving the central result of Krusell et al. (2000). The two substitution margins reduce the structural drag from 0.50 to approximately 0.4 percentage points and shrink it slightly over time as the economy reallocates away from structures-intensive production. They also reveal a previously unrecognized channel through which structures prices shape wage inequality: because structures and unskilled labor are substitutes, the rising relative price of structures raises the relative demand for unskilled labor and dampens the rise in the skill premium. A counterfactual exercise in the spirit of Krusell et al. (2000) that shuts down this margin yields a markedly higher skill-premium path. The canonical four-factor specification embeds structures as a Cobb–Douglas factor separable from the skill-complementary capital stock and therefore rules out this channel by construction. We find that ignoring this

[2] 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).

channel could overestimate the rise in the skill premium in the U.S. from 1963 to 2019 by 30%.

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.[3] 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 acts as a significant offsetting force.[4]

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 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.[5]

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 prices compared to advanced economies. This implies a dual effect on global inequality. While the equipment channel

[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).

[4] Our framework also engages with the cost-disease literature (Baumol, 1967). The ISTC literature has focused on falling equipment prices as a positive force on aggregate growth; the cost-disease literature has emphasized that rising relative prices in low-productivity sectors slow it. We connect the two by showing that structures play a cost-disease role on the capital side, raising the relative price of an essential input into both production and innovation. Our CES estimates further connect to this literature in a precise sense: the magnitude of the drag, and the rate at which it attenuates over time, depend on how easily the economy substitutes across input bundles with differential productivity growth.

[5] 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.

favors divergence as rich nations benefit more from falling technology costs, the structures 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 a "strange and awful path". Using KLEMS data, we show that this productivity decline is the primary driver of rising construction-sector relative prices, both in the United States and in other major economies. Our model then demonstrates that this decline constitutes a binding constraint on the aggregate economy, effectively bottling up the potential gains from the 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 analysis of the United States, we use the Fixed Assets Accounts tables from the Bureau of Economic Analysis (BEA).[6]

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[7] and structures.[8] 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.

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`)

[6]The definition of capital and the coverage of each dataset used in our analysis are discussed in Appendix A.

[7]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'.

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

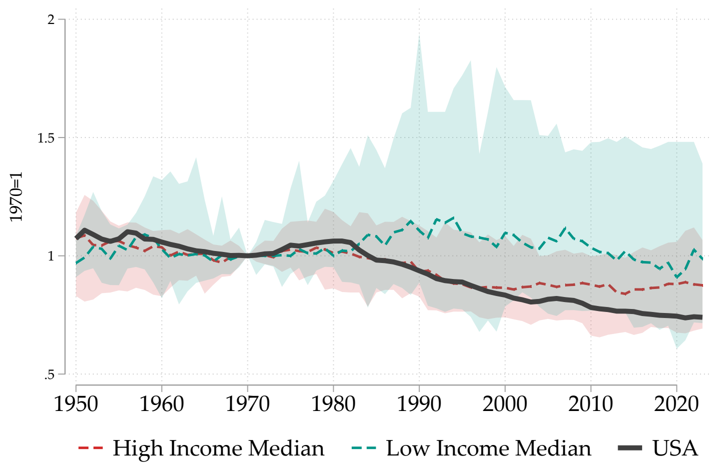
as our main measure of aggregate output and the TFP series (ctfp) to characterize productivity. To account for cross-country differences in labor quality, we include the human capital index (hc) as a control.[9] Finally, we use total population (pop) to control for scale.

2.2 Stylized Facts

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

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.

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

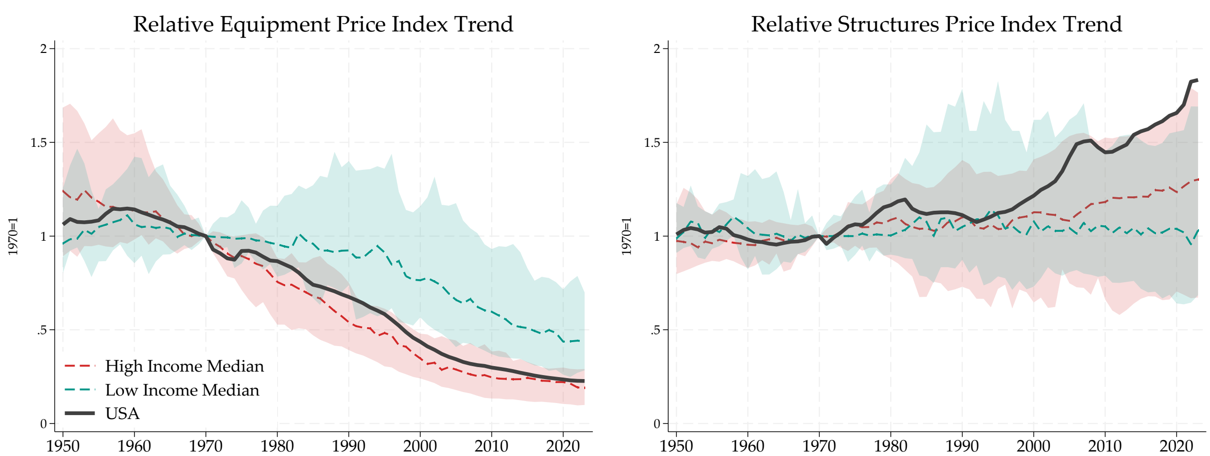
[9] We complement this measure with the PWT Labor Detail file, which provides more granular information on educational attainment. In particular, we use average years of schooling (yr_sch) primarily from Barro and Lee (2013).

low-income median (green dashed line) is above the high-income median (red dashed line) for much of the post-1980 period, indicating a modest but visible divergence.

However, disaggregating investment into equipment and structures reveals striking differences.[10] The left panel of Figure 2 plots the evolution of equipment prices. Equipment prices decline rapidly in both the United States and 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. By contrast, the low-income group displays a flat path.[11][12]

Figure 2: **Relative Investment Price Index Trend by Asset Type (1950–2020)**



Notes: The relative price for each asset type is calculated by dividing each type'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. *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

[10] PWT Capital Detail reports four different types of capital: Structures, Machinery and Equipment, Transport Equipment, and Other.

[11] Trends for the remaining asset categories (transport equipment and other assets) are reported in Appendix B.1.2.

[12] We obtain similar patterns when using capital-stock-based price indices for both asset types, as reported in Appendix B.1.3.

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 prices 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.[13]

Fact 2: Real investment rates in both asset types 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 allow us to identify the specific price levels and investment volumes for each asset type 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 asset type and GDP measured in real PPP terms.

We explicitly employ the ICP data to capture the cross-country dispersion in absolute price levels across asset types, 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.[14] 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

[13] Appendix B.1.4 reports the corresponding plots as well as the estimated coefficient changes in the cross-sectional regressions across survey years.

[14] The dataset widely used for cross-country analysis is the PWT. Its main advantage is that it provides PPP prices for investment and consumption, which makes it possible to study, in both cross section and panel settings, such as how relative investment prices affect growth (Jones, 1994; Restuccia and Urrutia, 2001). However, for the central purpose of this paper, to examine how equipment and structures differentially affect investment rates and growth, the PWT is not sufficient. Although the PWT reports disaggregated capital prices, these are expressed in local currency units and normalized so that a given reference year equals one in each country. This normalization generates a unit inconsistency that complicates cross country comparisons. We therefore use the ICP data. In addition, while ICP prices come from direct price surveys of standardized items conducted simultaneously across countries, PWT between benchmark years is interpolated using national accounts deflators. Hsieh and Klenow (2007) is an example of a study that uses disaggregated ICP data on investment (durable, which is matched with equipment in our setting, and structure) and consumption goods (tradable and nontradable) for cross-country analysis.

pooled regression model with country and 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 asset type 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, normalized by the exchange rate. The vector $\mathbf{X}_{it}$ includes country-specific controls such as human capital and population structure.[15] 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 the investment rate of asset type k. Specifically, the own-price coefficients $\beta_{\text{Equip}}^{\text{Equip}}$ and $\beta_{\text{Str}}^{\text{Str}}$ measure the direct impact of capital costs on accumulation within the same asset type, where 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 relationship across asset types. 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.

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.

First, we find evidence of negative own-price elasticities in both asset types. 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%.

[15] 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.

Table 1: **The Effect of Capital Prices on Investment Rates by Asset Type**

	Equipment Investment Rate (1)	Structures Investment Rate (2)
Log Equipment Price	-0.469***	0.369**
	(0.128)	(0.152)
Log Structures Price	0.255***	-0.632***
	(0.086)	(0.066)
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)
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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

These results confirm that higher capital costs directly dampen accumulation within the respective asset type. 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 may 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 prices show a much weaker association.

Having established the relationship between capital prices and each type's 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 predetermined 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. We estimate the effect of the current price measure on output at each horizon h, including the contemporaneous case $h = 0$, controlling for lagged GDP per capita with $\tau \in \{6, 10\}$.

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 an 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 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, in which prices strongly predict future growth but barely "predict" the past serves as a placebo test. Favorable equipment prices appear to precede and propel subsequent economic takeoff.

Second, the results highlight heterogeneity across capital asset types. While lower equipment prices are consistently associated with higher current and future income levels, the coefficients on structures prices are generally insignificant or economically small.

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 prices was broad-based across nearly all types of structures.

We now narrow our focus to the United States and document the evolution of investment prices at the level of BEA asset types.[16] Figure 3 highlights two contrasting

[16]BEA provides detailed asset-type price indexes, whereas the PWT Capital Detail provides only four categories: equipment, structures, transportation, and other assets. In Appendix A, we describe the coverage of each dataset in detail. In addition, Figure A.1 shows that the relative prices of equipment and structures

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

	Control: Lagged GDP ($t-6$)			Control: Lagged GDP ($t-10$)		
	$\ln(y_{i,t-5})$ (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)
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)
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)
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	✓	✓	✓	✓	✓	✓

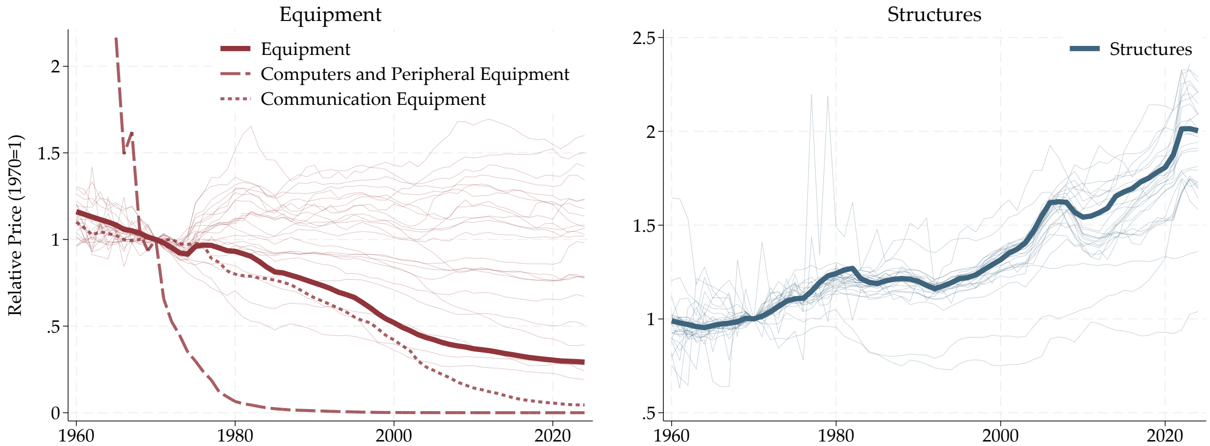
Notes: Standard errors are reported in parentheses and are clustered at the country level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Columns (1)–(3) control for lagged GDP per capita at $t-6$ ($\ln(y_{i,t-6})$), while columns (4)–(6) control for lagged GDP per capita at $t-10$ ($\ln(y_{i,t-10})$).

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 to 40%.[17] 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.,

reported by the BEA are broadly consistent with those in the PWT, which supports the use of both datasets.

[17]Refer to Appendix Table A.I for each asset's relative price and its 2020 investment share within the corresponding capital segment, measured as the asset's investment divided by total asset-class investment.

Figure 3: **Relative Investment Price Index Trend by Asset Type (1960-2020)**



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 GDP Deflator 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). Details of the asset classes are provided in Table A.I. The petroleum and natural gas structures category is omitted from the right panel. *Sources:* U.S. Bureau of Economic Analysis (BEA), BEA Fixed Assets Accounts Tables 2.7 and 2.8; Gross Domestic Product: Implicit Price Deflator (GDPDEF) from Federal Reserve Bank of St. Louis (FRED); and authors' calculations.

2020).

Second, in sharp contrast, the relative price of structures rises markedly after 1990, as shown in the right panel of Figure 3. This increase is not driven by a single structure type: the disaggregated series move upward together, indicating a broad-based rise across nearly all categories. This pattern suggests that post-1990 structures price dynamics reflect an economy-wide shift in the structures component of investment rather than compositional change within structures.[18]

Table 3 summarizes, for 2020, the ten BEA asset categories with the highest investment shares in each asset class and shows how total investment is allocated across these categories within the broad groups of equipment and structures. It also reports their relative prices in 2020, where each asset's real price in 1970 is normalized to 1. The table shows that equipment prices are largely driven by the rapid price declines of information and communication technology-related equipment, whereas structures exhibit similar patterns across sub-asset classes and are not concentrated in residential housing. All

[18]These results are robust to using BEA price indices constructed from the current-cost net stock series, as reported in Appendix B.2.

sub-asset classes are reported in Appendix Table A.I.

Table 3: **Investment Shares by BEA Asset Category and Relative Prices in 2020**

Asset Class	**Share**	**Price**	**Asset Class**	**Share**	**Price**
Equipment	100%	0.304	Structures	100%	1.808
Communication Equipment	10.96%	0.06	Housing (1 To 4 Unit)	21.47%	1.72
Computers (Peripheral Equip.)	10.92%	<0.01	Improvements	19.78%	1.55
Medical Equip.	9.57%	0.43	Brokers' Commission	12.90%	1.87
Light Trucks	9.45%	0.76	Office	6.17%	1.91
General Industrial Machinery	8.26%	1.06	Electric	5.67%	1.72
Other Nonresidential Equip.	6.45%	0.77	Housing (5 Or More)	5.54%	2.14
Electrical Transmissions	4.27%	0.76	Manufacturing	5.00%	1.74
Furniture And Fixtures	4.09%	1.01	Petroleum / Natural Gas	3.97%	4.40
Other Trucks, Buses, etc	3.80%	1.21	Warehouses	2.85%	1.87
Special Industry Machinery	3.79%	1.22	Lodging	2.28%	1.77

Notes: **Share** denotes each detailed BEA asset category's share of total 2020 investment within the corresponding asset type, Equipment or Structures. **Price** is the ratio of the asset's real price in 2020 to its real price in 1970, where real prices are nominal prices deflated by the GDP deflator and the 1970 level is normalized to 1. Within each broad group, categories are ordered in descending order of **Share**.

2.3 Why Have Structures Prices Increased? Construction Productivity

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 in the construction sector. We find that the Bureau of Labor Statistics (BLS) 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.[19]

Several factors may have contributed to stagnant construction productivity. For example, Goolsbee and Syverson (2023) showed that construction firms' abilities to turn materials into output have 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 incentives

[19]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.

to invest in innovation.[20]

To assess the extent to which the rise in construction-sector prices reflects productivity decline, we use the U.S. data from the EU KLEMS dataset to decompose the relative output price of construction into input cost and TFP components. EU KLEMS also offers harmonized cross-country coverage under a common industrial classification, making it well suited to a comparative analysis of construction-sector price dynamics within a unified framework.

We decompose the construction sector output price using the Törnqvist approach within a duality framework.[21] This decomposition follows from the duality between the production function and the cost function under constant returns to scale and competitive factor markets. The primal identity states that output growth equals the share-weighted sum of input growth and TFP growth. Its dual counterpart expresses output price growth as the share weighted sum of input price growth minus TFP growth. Accordingly, under constant returns to scale and competitive factor markets, the gross-output price of sector i, P_i, satisfies the following unit-cost identity:

$$\Delta \ln P_i = \bar{s}_{L,i}\,\Delta \ln P_{L,i} + \bar{s}_{K,i}\,\Delta \ln P_{K,i} + \bar{s}_{II,i}\,\Delta \ln P_{II,i} - \Delta \ln A_i, \tag{3}$$

where $\bar{s}_{j,i}$ denotes the Törnqvist two-period average cost share of input j in gross output, $P_{j,i}$ denotes the price of input j, and $\Delta \ln A_i$ denotes TFP growth in sector i. Subtracting $\Delta \ln P_{agg}$ from both sides yields the following expression

$$\Delta \ln\left(\frac{P_i}{P_{agg}}\right) = \mathrm{rel}_{L,i} + \mathrm{rel}_{K,i} + \mathrm{rel}_{II,i} - \Delta \ln A_i,$$

where each relative input cost term is defined as $\mathrm{rel}_{j,i} \equiv \bar{s}_{j,i}\left(\Delta \ln P_{j,i} - \Delta \ln P_{agg}\right)$. Accordingly, each relative cost term measures the contribution of sector specific input price movements, relative to the aggregate price level, to the sector's relative output price change.[22]

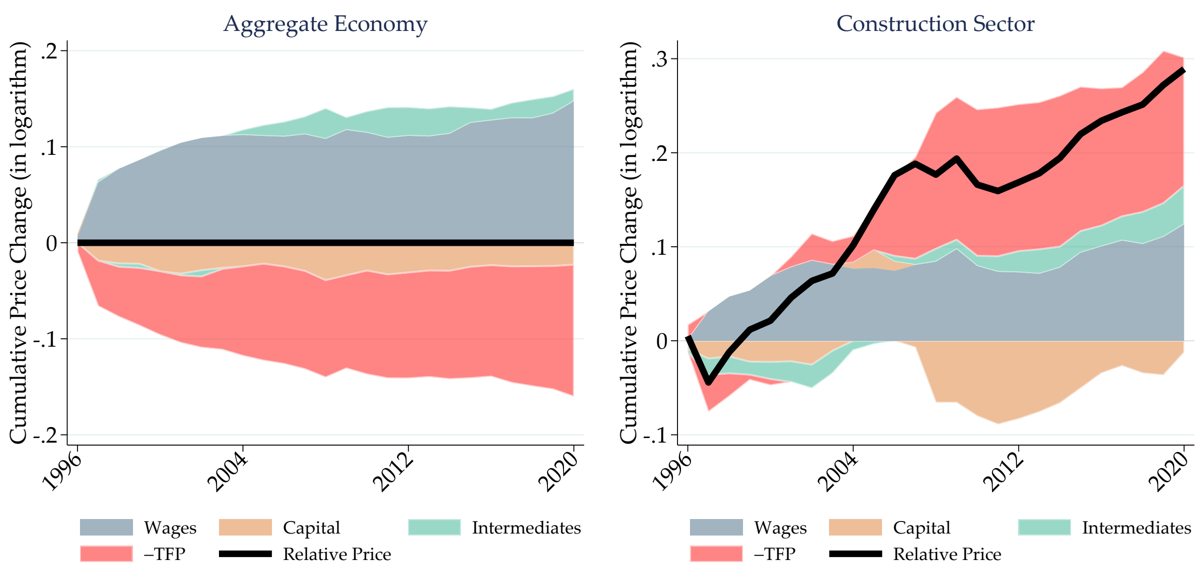
[20]The productivity problem also appears in the public sector. Brooks and Liscow (2023) find that spending per mile in the Interstate Highway System increased more than threefold from the 1960s to the 1980s.

[21]Additional details on the Törnqvist approach are provided in Appendix C.1. Because the Törnqvist index has a duality foundation, we use the dual approach for two reasons. First, our question is price based, since it asks why construction prices have risen faster than the general price level. The dual formulation maps this directly into cost drivers such as labor, capital, intermediate inputs, and productivity. Second, industry output quantities are often measured with greater error or constructed by deflating nominal values, while input prices and cost shares are generally more reliable in the national accounts.

[22]Labor contribution (rel_L) reflects sector specific labor cost pressure relative to the aggregate price level, capital contribution (rel_K) reflects relative capital service cost pressure, and intermediate input contribution (rel_{II}) reflects relative price pressure from purchased materials and services. Positive values indicate that the corresponding input cost rises faster than the aggregate benchmark and therefore pushes the sector's

Figure 4 presents a decomposition of the cumulative change in output prices, $\sum \Delta \ln(P_i/P_{agg})$, using 1996 as the base year and cumulating annual changes through 2020, into relative input-cost components and TFP for both the aggregate economy and the construction sector. The aggregate level decomposition is included for comparison with the construction sector. Note that, by construction, the decomposition in the aggregate output-price panel, $\sum \Delta \ln(P_{agg}/P_{agg})$, sums to zero.

Figure 4: **Decomposition of Relative Prices: Aggregate vs. Construction Sector**



Notes. The figure presents a cumulative decomposition of sectoral gross-output prices relative to the aggregate economy in the United States within the Törnqvist dual framework. The left panel reports the aggregate economy, while the right panel presents the construction sector. Each shaded area denotes the cumulative log-point contribution of a given channel to the change in a sector's gross-output price relative to the aggregate economy since the beginning of the sample. The productivity component, $(-\Delta \ln A)$, is defined as the negative of the dual total factor productivity residual. A negative value indicates that productivity growth offsets input-cost pressures and lowers the relative price. Accordingly, the −TFP area captures the contribution of productivity shortfalls rather than productivity gains. The black line, $\sum \Delta \ln(P_i/P_{agg})$, traces the cumulative change in the sector's gross-output price relative to the aggregate economy. *Sources:* EU KLEMS 2024 and authors' calculations.

The aggregate panel on the left provides a useful benchmark. Although labor costs make a positive contribution at the aggregate level, this upward pressure is offset by TFP growth and movements in capital costs. The construction sector presents a clear contrast. In the construction sector, the positive contribution of labor costs is not accompanied by an offsetting productivity component. Instead, the contribution of negative TFP is itself strongly positive, indicating that weak productivity growth amplified rather than

relative output price upward.

absorbed cost pressures. Intermediate input costs also push relative prices upward, while the capital component is negative over part of the sample and therefore provides only limited relief.[23]

Cross-country Evidence We repeat the same exercise for other countries using KLEMS data to examine whether the role of TFP in driving construction price increases is specific to the United States. Figure 5 plots each country's cumulative TFP growth against its cumulative change in the relative construction price, accumulated from 1995 through 2021 (2020 for the United States, the United Kingdom, and Japan; 1999–2021 for Belgium), and provides a cross-sectional summary of their correlation.[24] The figure shows that cumulative construction-sector TFP growth is negatively correlated with cumulative changes in relative construction prices across countries. Most countries experienced both an increase in relative construction prices and a decline in cumulative construction-sector TFP; Belgium is the one exception, with both magnitudes close to zero. On average across those thirteen economies, the decline in TFP accounts for 59% of the increase in relative construction prices, while the corresponding share for the United States is 47%.[25]

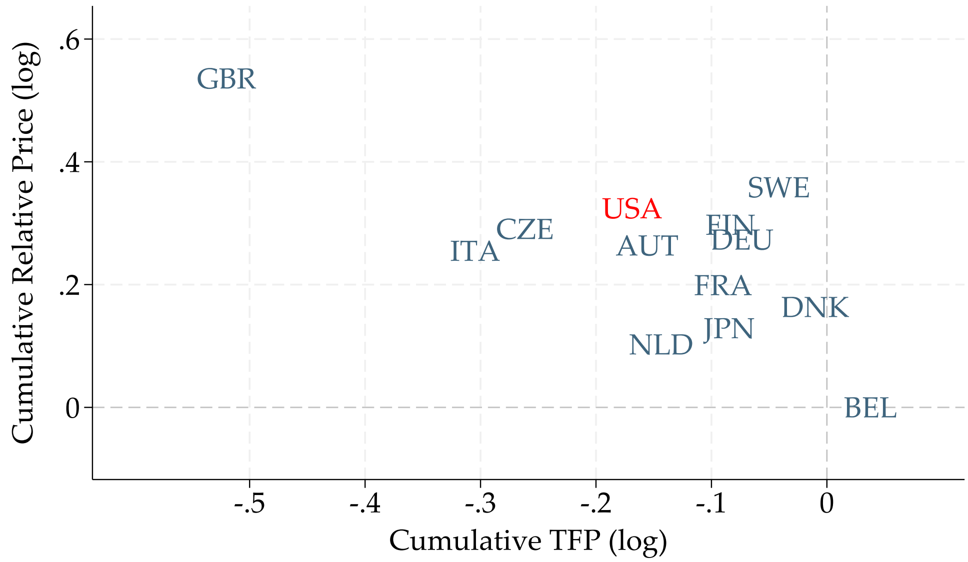
These results suggest that the rise in relative prices in the construction sector cannot be understood simply as an increase in input costs. Rather, the key distinction from the aggregate economy is the absence of offsetting productivity growth in construction. In this sense, the results provide direct support for the view that the increase in construction prices after 1990 is closely linked to the productivity slowdown in the U.S. construction sector (Goolsbee and Syverson, 2023), which raises the effective cost of accumulating structures.

[23] This pattern is also consistent with the value-added growth decomposition reported in Appendix C.2. At the aggregate level, value added growth is driven largely by TFP growth, whereas in construction TFP acts as a drag on value added growth.

[24] The cross section includes 13 economies, the United States, Japan, Germany, France, the United Kingdom, Italy, Austria, Belgium, the Czech Republic, Denmark, Finland, the Netherlands, and Sweden. The cumulative window is 1995–2021, except for the United States, the United Kingdom, and Japan, which end in 2020, and Belgium, which begins in 1999 because its construction labor quantity index is unavailable earlier. We use gross-output decompositions except for the United Kingdom and Italy, for which EU KLEMS 2024 does not provide continuous gross-output deflators, so we retain these reference economies with the value-added analogue. Bulgaria, Cyprus, Ireland, Lithuania, Malta, Slovakia, Slovenia, and Spain are excluded for the same gross-output limitation. Croatia, Hungary, Poland, Portugal, and Romania lack construction labor and capital quantity indexes, while Estonia, Greece, Latvia, and Luxembourg begin only in 2008 for construction labor quantity.

[25] Appendix C.3 further decomposes and plots cumulative changes in relative construction prices into cost-pressure and TFP contributions for the United States, Japan, Germany, France, Italy, and the United Kingdom. The results show that, regardless of the accumulation period considered, declines in construction-sector TFP consistently contribute to increases in relative construction prices across major economies. This pattern is therefore not confined to a particular year, but reflects a persistent cross-country feature.

Figure 5: **Cross-Country Construction Relative Prices vs. Productivity**



Notes. The figure plots each country's cumulative TFP growth against its cumulative change in the relative construction price, accumulated from 1995 through 2021 (2020 for the United States, the United Kingdom, and Japan; 1999–2021 for Belgium), and provides a cross-sectional summary of the same decomposition. The cross section covers the United States, Japan, Germany, France, the United Kingdom, Italy, Austria, Belgium, the Czech Republic, Denmark, Finland, the Netherlands, and Sweden. The decomposition is based on gross output for all countries except the United Kingdom and Italy, where value added is used because gross-output price indexes are unavailable in the 2024 EU KLEMS release. *Sources.* EU KLEMS 2024 and authors' calculations.

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 three channels: it reduces capital deepening in production, increases R&D facility costs, and tightens economy-wide resources for 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:

$$P_E(t) \equiv \frac{1}{q_E(t)}, \qquad P_S(t) \equiv \frac{1}{q_S(t)}. \tag{4}$$

Capital stocks evolve according to

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

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:

$$\frac{\dot{q}_E(t)}{q_E(t)} = \gamma_E, \qquad \frac{\dot{q}_S(t)}{q_S(t)} = \gamma_S. \tag{5}$$

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 require $K_E(t) = K_E^Y(t) + K_E^R(t)$ and $K_S(t) = K_S^Y(t) + K_S^R(t)$.

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

$$Y(t) = A(t) \left(K_E^Y(t)\right)^{\alpha_E} \left(K_S^Y(t)\right)^{\alpha_S} \left(L_u(t)\right)^{1-\alpha_E-\alpha_S}. \tag{6}$$

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

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

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 determine the evolution of aggregate productivity $A(t)$. The sector uses equipment capital (K_E^R), structures (K_S^R), and skilled labor (L_s). In the baseline model, the R&D allocation is characterized as a planner-equivalent allocation, rather than as the problem of a decentralized firm selling a traded claim to knowledge. This formulation follows the production-possibilities approach of Jones and Williams (1998), in which the social return to research is derived from the idea-production technology and the final-output production technology, without imposing a particular market structure or patent arrangement for knowledge.

Knowledge production is given by

$$\dot{A}(t) = \kappa\, A(t)^{\phi} \left(K_E^R(t)\right)^{\eta_E} \left(K_S^R(t)\right)^{\eta_S} \left(L_s(t)\right)^{1-\eta_E-\eta_S}. \tag{7}$$

Let $A(t)$ denote the aggregate stock of knowledge and let $p_A(t)$ denote the final-good-denominated current-value shadow value of a marginal increase in aggregate knowledge. In the baseline model, $A(t)$ is not a traded asset and does not generate a direct payment stream in the household budget constraint. Accordingly, $p_A(t)$ is interpreted as the current-value shadow value of the aggregate knowledge stock, not as the price of a privately traded knowledge asset (Jones and Williams, 1998).[26]

Since $A(t)$ enters both final-goods production and the law of motion for knowledge, its social shadow value reflects both its direct contribution to current final output and its indirect contribution to future knowledge production. The current-value costate equation is

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

Using $\partial Y(t)/\partial A(t) = Y(t)/A(t)$ and $\partial \dot{A}(t)/\partial A(t) = \phi \dot{A}(t)/A(t)$, this becomes

$$\dot{p}_A(t) = r(t)p_A(t) - \frac{Y(t)}{A(t)} - \phi p_A(t)\frac{\dot{A}(t)}{A(t)}. \tag{9}$$

The term $Y(t)/A(t)$ is the direct marginal product of aggregate knowledge in final-goods production. The term $\phi p_A(t)\dot{A}(t)/A(t)$ captures the social value of the knowledge spillover in future R&D productivity. Since $A(t)$ is specified as an aggregate state variable whose

[26] If one instead introduced tradable claims to individual designs, the relevant dividend in the no-arbitrage condition would be the profit flow associated with a marginal design, denoted by $\pi_A(t)$. The corresponding asset-pricing equation would be $r(t)p_A(t) = \pi_A(t) + \dot{p}_A(t)$, where $\pi_A(t)$ is the profit flow accruing to the owner of a marginal design under an explicit licensing or monopolistic-competition micro-foundation such as Romer (1990) and Jones (1995). This alternative assumption regarding the R&D sector does not affect the BGP derived in the main text.

value is summarized by the costate variable $p_A(t)$, this term should be interpreted as part of the shadow valuation of aggregate knowledge rather than as a dividend payment.

At each time t, the R&D allocation equates the social value of marginal knowledge production to the opportunity costs of R&D inputs. The static allocation condition can be written as

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

The corresponding first-order conditions are

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

These are shadow allocation conditions and the term $p_A(t)\dot{A}(t)$ summarizes the social value of knowledge production within the allocation problem.

3.3 Households

Population $N(t)$ grows at a constant exogenous rate n, $\dot{N}(t) = nN(t)$. We normalize the labor endowment per capita to unity, such that total labor supply equals population size, $L(t) = N(t)$. An exogenous 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, households supply labor inelastically and own the economy's physical capital stocks. Let $w_s(t)$ and $w_u(t)$ denote the wage rates for skilled and unskilled labor, and let $R_E(t)$ and $R_S(t)$ denote rental rates per unit of physical equipment and structures. These rental rates are distinct from the final-good-denominated real interest rate $r(t)$. The R&D block is treated as a planner-equivalent allocation, so it generates no separate private revenue or profit rebate to households.

The representative household maximizes

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

where $c(t) = C(t)/N(t)$, $\rho > 0$, and $\sigma > 0$. The household budget constraint is

$$C(t) + I_E(t) + I_S(t) = w_s(t)L_s(t) + w_u(t)L_u(t) + R_E(t)K_E(t) + R_S(t)K_S(t).$$

The household's intertemporal optimality condition implies

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

No arbitrage requires that the total 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

$$r(t) = \frac{R_E(t)}{P_E(t)} + \frac{\dot{P}_E(t)}{P_E(t)} - \delta_E = q_E(t)R_E(t) - \gamma_E - \delta_E, \tag{10}$$

$$r(t) = \frac{R_S(t)}{P_S(t)} + \frac{\dot{P}_S(t)}{P_S(t)} - \delta_S = q_S(t)R_S(t) - \gamma_S - \delta_S. \tag{11}$$

3.4 Balanced Growth Path (BGP)

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

$$\Delta \equiv (1 - \phi)(1 - \alpha_E - \alpha_S) - (\eta_E + \eta_S) > 0. \tag{12}$$

On a BGP, aggregate quantities $(Y, C, I_E, I_S, K_E, K_S)$ grow at constant rates, and 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 system:

$$g_Y = g_A + \alpha_E(g_Y + \gamma_E) + \alpha_S(g_Y + \gamma_S) + (1 - \alpha_E - \alpha_S)n, \tag{13}$$

$$(1 - \phi)g_A = (\eta_E + \eta_S)g_Y + \eta_E\gamma_E + \eta_S\gamma_S + (1 - \eta_E - \eta_S)n. \tag{14}$$

Solving (13) for g_Y delivers a decomposition:

$$g_Y = n + \underbrace{\frac{1}{1-\alpha_E-\alpha_S} g_A}_{\text{TFP contribution}} + \underbrace{\frac{\alpha_E\gamma_E+\alpha_S\gamma_S}{1-\alpha_E-\alpha_S}}_{\text{ISTC-induced deepening}}. \tag{15}$$

Substituting (15) into (14) yields the endogenous TFP growth rate:

$$g_A = \frac{(1-\alpha_E-\alpha_S)n + \big(\eta_E(1-\alpha_S)+\eta_S\alpha_E\big)\gamma_E + \big(\eta_S(1-\alpha_E)+\eta_E\alpha_S\big)\gamma_S}{(1-\phi)(1-\alpha_E-\alpha_S)-(\eta_E+\eta_S)}. \tag{16}$$

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 asset-type 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 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 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 composition as a simple empirical proxy to split the aggregate capital income share across asset types.[27]

[27] Along the balanced growth path, investment-flow composition can be derived as $\frac{I_E/I_S}{\alpha_E/\alpha_S} = \frac{g_Y+\delta_E}{g_Y+\delta_S} \cdot \frac{r+\delta_S}{r+\delta_E}$.

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 BERD data from 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 account for the remaining $\eta_S = 0.07$.[28] Table 4 reports all the calibrated parameters used in the numerical analysis.

4.2 Model Performance

We first assess the calibrated model's fit to U.S. growth from 1970 to 2020, then quantify the impact of structural drag on long-run growth. Figure 6 compares the simulated series with the empirical data.

Targeted Moments: Asset-Type Prices The top panels of Figure 6 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 prices, 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 BLS, respectively. The calibrated model closely matches the observed growth paths of GDP per capita and the TFP stock.

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. In the United States, the equipment share is about 38.8% in 2015, which pins down α_E at 0.1469. Figure B.2 shows that the equipment share is stable across countries despite variation in income, implying that the allocation of investment between equipment and structures is relatively stable across countries as well. Finally, Figure B.3 shows the U.S. trend in the share of equipment investment out of total investment in equipment and structures, which remains stable.

[28] We use the observed composition of R&D capital spending as a proxy to allocate the aggregate R&D capital share across equipment and structures. Figure A.2 shows the time series of the equipment investment share in the R&D sector, and the share has remained around 80% since 2015. Figure A.3 illustrates that the composition of R&D capital expenditures is stable across countries as well, with equipment accounting for roughly 80% of total equipment-plus-structures spending over a wide range of income levels.

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 of relative Equipment price growth (TFP)	0.0290	PWT (1970–2020)
γ_S	Inverse of relative Structures price growth (TFP)	−0.0101	PWT (1970–2020)
δ_E	Depreciation Rate of Equipment	0.130	BEA (1970–2020)
δ_S	Depreciation Rate of Structures	0.030	BEA (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. The table summarizes the baseline parameterization for the U.S. economy. Together, these values discipline the balanced-growth implications used in the quantitative exercises.

4.2.1 Benchmark Comparisons

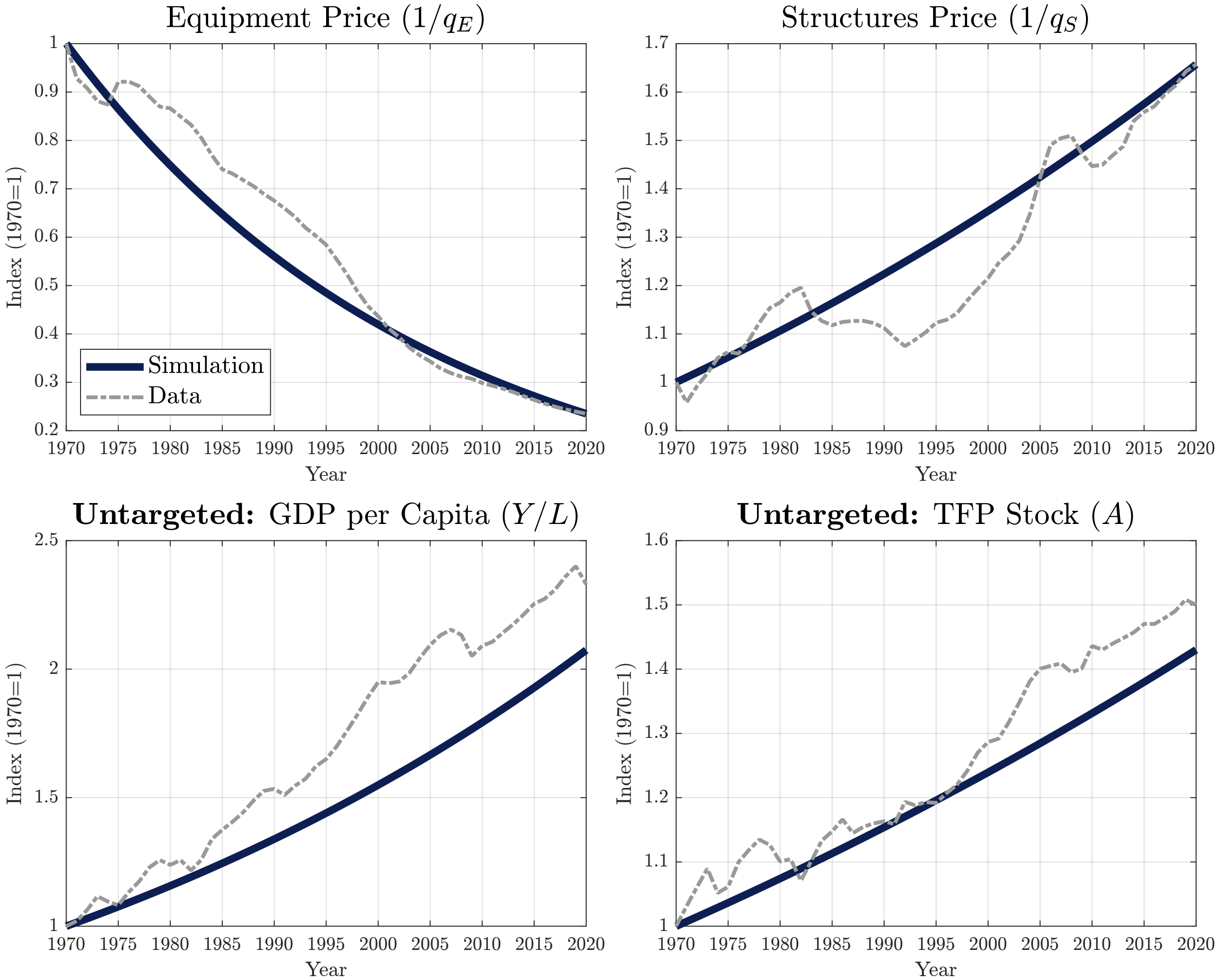
Our model introduces two new margins relative to standard growth frameworks: capital heterogeneity (equipment versus structures) and the use of capital in the R&D sector. To assess the quantitative importance of these margins, we compare our baseline specification to commonly used benchmarks, including a neoclassical one-capital growth model and a Romer-type model. We show that our model delivers GDP per capita growth rates that are closer to the U.S. data than these alternative specifications. Additional details and model comparisons are provided in Appendix E.

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 (15) with the closed-form expression for g_A in (16), and defining per-capita output growth as $g_y \equiv g_Y - n$, yields the linear representation

$$g_y = \mu_n^y \cdot n + \mathcal{M}_E \cdot \gamma_E + \mathcal{M}_S \cdot \gamma_S. \tag{17}$$

Figure 6: **Baseline Simulation. Asset-Type 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/L) and the TFP stock (A). The asset-type 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.

The coefficients in (17) are interpretable multipliers that map observed trend components into long-run per-capita growth. Grouping terms by n, γ_E, and γ_S implies

$$\mu_n^y \equiv \frac{1}{\Delta}, \qquad \mathcal{M}_E \equiv \frac{\alpha_E}{\Psi} + \frac{\eta_E(1-\alpha_S)+\eta_S\alpha_E}{\Psi\,\Delta}, \qquad \mathcal{M}_S \equiv \frac{\alpha_S}{\Psi} + \frac{\eta_S(1-\alpha_E)+\eta_E\alpha_S}{\Psi\,\Delta}, \tag{18}$$

where $\Psi \equiv 1-\alpha_E-\alpha_S$ and $\Delta \equiv (1-\phi)\Psi - (\eta_E+\eta_S)$ as in (12). 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 through induced innovation. The structures 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 (16).

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:

$$\mathcal{M}_S = \underbrace{\frac{\alpha_S}{\Psi}}_{\text{Static Deepening}} + \underbrace{\underbrace{\frac{\eta_S(1-\alpha_E)}{\Psi\,\Delta}}_{\text{Direct Input Channel}} + \underbrace{\frac{\eta_E\alpha_S}{\Psi\,\Delta}}_{\text{Indirect Resource Channel}}}_{\text{R\&D-related Structural Drag}} \tag{19}$$

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 (19) 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 (17) together with the structures-channel split in (19). Table 5 reports the resulting contributions in percentage points (pp) per year.

Per-capita output grows by 1.46 pp per year, driven by population growth (0.64 pp)

Table 5: **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.

and equipment-specific ISTC (1.32 pp), while structures subtract 0.50 pp, offsetting about 38% of the equipment boost.

Table 6: **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.

As shown in Table 6, 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 (19): the direct input channel accounts for 49.6% (−0.06 pp) and the indirect resource channel accounts for 50.4% (−0.06 pp).

4.4 Sensitivity Analysis on Structural Drag

We conduct a sensitivity analysis by varying three parameters that govern the strength and composition of the model's growth channels. Specifically, we vary the knowledge-spillover parameter, ϕ, the output elasticity of structures, α_S, and the R&D elasticity of structures, η_S.[29] When varying α_S and η_S, we hold fixed the total capital share, $\alpha_E + \alpha_S$, and the total R&D input elasticity, $\eta_E + \eta_S$, respectively.

Table 7 examines how the quantitative importance of structural drag changes under alternative values of key parameters. The sensitivity analysis shows that structural drag remains quantitatively important across all specifications. In the baseline calibration, structural drag reduces per-capita output growth by 0.50 percentage points per year, while the equipment boost raises per-capita output growth by 1.32 percentage points per year. Thus, the decline in structures-specific investment technology offsets about 38% of the positive growth contribution from equipment-specific investment technology. This result is not driven by a narrow parameter choice. Across the alternatives reported in the table, structural drag remains negative and offsets a sizable fraction of the equipment boost.

Panel (A) shows that as ϕ becomes more negative, induced innovation weakens and both structural drag and the equipment boost shrink in absolute value. Structural drag remains important, however, with the offset ratio rising from 25.77% at $\phi = 0$ to 42.97% at $\phi = -4$. In addition, the per-capita output growth rate g_y is highly sensitive to the value of ϕ. As ϕ increases from −4 toward 0, we observe a significant acceleration in growth, from 0.94 pp per year to 6.37 pp per year.

Panel (B) shows that increasing α_S strengthens structural drag and reduces the equipment boost because the total capital share is fixed. As α_S rises from 0.17 to 0.29, structural drag increases from 0.38 to 0.62 pp per year, the equipment boost falls from 1.67 to 0.99 pp per year, and the offset ratio rises from 22.86% to 62.46%.

Panel (C) shows that increasing η_S has similar effects. As η_S rises from 0.02 to 0.12, structural drag increases from 0.47 to 0.54 pp per year, the equipment boost falls from

[29] The candidates for ϕ values are drawn from Jones (2022). 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 $\phi \equiv 1 - \beta$. In the Jones (2022) specification $\dot{A}/A = A^{-\beta}$, β measures the strength of diminishing research opportunities: when $\beta > 0$, a higher technology level A reduces the proportional growth rate. In our specification $\dot{A} = A^{\phi}$, ϕ governs the curvature (returns to scale) of knowledge production and $\phi < 1$ implies diminishing returns. Therefore, the higher β is, the lower the ϕ is. 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, $\Delta > 0$ (equation (12)).

Table 7: **Sensitivity of Structural Drag and Equipment Boost to Key Parameters**

	Structural Drag (pp/year)	Equipment Boost (pp/year)	|Drag|/Boost (%)	g_y (pp/year)
Panel A. Knowledge spillover ϕ				
$\phi = 0.0$	-1.044	4.050	25.77	6.370
$\phi = -1.0$	-0.589	1.758	33.49	2.242
$\phi = -2.0^*$	-0.502	1.324	37.91	1.460
$\phi = -4.0$	-0.446	1.037	42.97	0.944
Panel B. Output elasticity of structures α_S				
$\alpha_S = 0.170$	-0.382	1.669	22.86	1.926
$\alpha_S = 0.200$	-0.441	1.499	29.40	1.697
$\alpha_S = 0.231^*$	-0.502	1.324	37.91	1.460
$\alpha_S = 0.260$	-0.559	1.160	48.21	1.239
$\alpha_S = 0.290$	-0.618	0.990	62.46	1.010
Panel C. R&D elasticity of structures η_S				
$\eta_S = 0.020$	-0.470	1.417	33.13	1.586
$\eta_S = 0.045$	-0.486	1.370	35.48	1.522
$\eta_S = 0.070^*$	-0.502	1.324	37.91	1.460
$\eta_S = 0.095$	-0.519	1.276	40.68	1.395
$\eta_S = 0.120$	-0.535	1.228	43.58	1.331

Notes. Structural drag, equipment boost, and g_y are reported in percentage points per year. The ratio |Drag|/Boost reports the share of the equipment boost offset by structural drag. Panel (A) varies the knowledge-spillover parameter, ϕ. Panel (B) varies the output elasticity of structures, α_S, while holding $\alpha_E + \alpha_S = 0.378$ fixed, so the output elasticity of equipment, α_E, adjusts accordingly. Panel (C) varies the R&D elasticity of structures, η_S, while holding $\eta_E + \eta_S = 0.331$ fixed, so the R&D elasticity of equipment, η_E, adjusts accordingly. The asterisk marks the baseline calibration.

1.42 to 1.23 pp per year, and the offset ratio rises from 33.13% to 43.58%. Overall, the structural-drag mechanism remains robust across the parameter values considered.

4.5 Measurement Error Adjustment

While the decline in construction sector productivity may be one driver of rising structures prices, as discussed in Section 2.3, a concern remains that the secular increase in the relative price of structures may, at least in part, reflect deflator mismeasurement rather than a genuine decline in construction productivity.[30] Even though Goolsbee and Syverson (2023) conclude that the weak performance of the construction sector is not merely a figment of measurement error, the structures price index may still miss improvements in

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

the unobserved quality of structures.[31]

Garcia and Molloy (2025) assess the extent to which the measured growth of construction costs is biased upward by improvements in unobserved structure quality. Their analysis centers on new single-family homes, the one sub-asset class for which structure quality is observable and can be adjusted, and bounds the bias in the single-family house price index using three approaches. First, they compare the index with detailed construction-cost estimates from R.S. Means that hold a rich set of structural characteristics fixed, a comparison that implies a negligible bias. Second, they use measures of structure quality not employed by the official index, namely property-tax-assessor and resident quality ratings together with an estimate of energy efficiency, which imply a bias of about 0.5 percentage points per year. Third, they apply the econometric bounding technique of Oster (2019), which yields an upper bound of 0.8 percentage points per year. The three approaches thus bracket the bias in the single-family price index between roughly zero and 0.8 percentage points per year.

The single-family house price index deflates less than half of nominal construction output, so its bias cannot be carried one-for-one to the economy-wide price of structures.[32] Garcia and Molloy (2025) carry the single-family upper bound to the aggregate construction sector and estimate an upper bound of total bias in measured construction prices at roughly 0.5 percentage points per year.

We borrow this aggregate range and revisit the size of structural drag. In our calibration, structures ISTC is proxied by the relative-price trend of structures, which rises by about 1 percentage point per year, and the implied structural drag is $\mathcal{M}_S\gamma_S = 0.50$ percentage points per year. Because the structural drag is linear in γ_S, removing a measurement-error component from the price trend scales the drag proportionally. Attributing 0.5 percentage points of the 1 percentage point trend to mismeasured quality leaves a genuine trend of 0.5 percentage points and a structural drag of about 0.25 percentage points per year.

At the lower end of Garcia and Molloy (2025)'s range the bias is negligible and the structural drag is undiminished at 0.50 percentage points. The upper end is a deliberately generous bound, resting on the permissive unobservable-selection assumptions built into the Oster (2019) bounding method, yet even under this strong correction a substantial structural drag of 0.25 percentage points still survives.

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

[32] In Garcia and Molloy (2025), the single-family house price index is used to deflate about 46 percent of nominal construction output, spanning new single-family construction, residential improvements, and part of nonresidential construction.

4.6 Counterfactual Analysis

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 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)**
Low Income	1.66%	−0.08%
High Income	3.02%	−0.42%
The United States	2.90%	−1.01%

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

What would have happened if the U.S. had faced different ISTC rates? We feed the region-specific ISTC pairs from Table 8 into the U.S.-calibrated model as counterfactual shocks, holding other parameters fixed. 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**	$g_y^{\textbf{ISTC}}$
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 median scenario, the U.S. growth shortfall is driven almost entirely by the structures margin. The equipment contribution is slightly larger under the high-income scenario (1.38pp vs. 1.32pp), but the U.S. experiences a much more severe structural drag (−0.50pp vs.

−0.21pp). Second, relative to the low-income median scenario, the U.S. outcome reflects offsetting forces: a larger equipment contribution (1.32pp vs. 0.76pp) is partly offset by a more negative structures contribution.

5 Extension: CES Output Technology

The baseline model makes two simplifying assumptions: a Cobb–Douglas production function across all factors, and a strict division of labor in which unskilled workers enter only production and skilled workers enter only research. In practice, however, both skill types interact with both types of capital, and the substitution patterns between labor and capital are central to how factor prices and quantities respond to investment-specific technological change, as emphasized by Krusell et al. (2000).

We therefore generalize the production function to a nested CES structure in which two capital–labor bundles are combined to produce output, $Y = AQ$ where the top nest aggregates an equipment–skilled-labor bundle M and a structures–unskilled-labor bundle S,

$$Q = \left[\omega M^{\rho_0} + (1-\omega) S^{\rho_0}\right]^{1/\rho_0}, \qquad \rho_0 \equiv \frac{\sigma_0 - 1}{\sigma_0}, \tag{20}$$

and

$$M = \left[\theta_M (K_E^Y)^{\rho_M} + (1-\theta_M) L_s^{\rho_M}\right]^{1/\rho_M}, \quad S = \left[\theta_S (K_S^Y)^{\rho_S} + (1-\theta_S) L_u^{\rho_S}\right]^{1/\rho_S} \tag{21}$$

where $\rho_j \equiv (\sigma_j - 1)/\sigma_j$ for $j \in \{M, S\}$.

The parameter ω governs the weight on M relative to S in the top nest. Within each bundle, θ_M and θ_S govern the weight on capital relative to labor. The elasticities σ_0, σ_M, and σ_S allow substitution patterns to differ across nests.[33]

Note that this differs from Krusell et al. (2000), where structures enter Cobb–Douglas and only the equipment–skilled-labor margin is modeled as CES. Our specification instead places structures inside a CES bundle with unskilled labor, allowing the structures–labor substitution elasticity to be estimated rather than restricted to one.

It is worth noting that this extension preserves the baseline structural-drag channel emphasized in the Cobb–Douglas case, but it no longer restricts the effect of structures ISTC to operate through a fixed loading coefficient. Because the CES structure makes factor shares endogenous, changes in structures ISTC affect output growth not only through the direct drag channel but also through additional reallocation margins

[33] We focus on the output side rather than the R&D production function because evidence on labor–capital interactions in R&D is limited, and detailed input data are scarce: the BERD survey reports capital expenditure breakdowns only from 2015 onward.

across and within bundles. Furthermore, this framework is rich enough to analyze how structures affect the skilled wage premium on top of equipment-skilled-labor complementarity, which we discuss in the following section.

5.1 Estimation Results for the CES Output Function

We begin by estimating the CES output function following Ohanian et al. (2023). We use annual U.S. sector-level data for the period 1963 to 2019, including sector-specific capital, labor hours, and wage data constructed by Ohanian et al. (2023). Because our specification estimates an additional parameter, the elasticity of substitution between structures and unskilled labor, we supplement their data with a structures-price series based on the investment-based structures price constructed from BEA Fixed Assets Accounts Tables and deflated by the GDP deflator.[34] The parameters are estimated by GMM using three sets of model-implied restrictions as in Ohanian et al. (2023). The first restriction equates the return on structures and the return on equipment. The second matches the aggregate labor share, using the gross labor share. The third matches the skilled-to-unskilled wage bill ratio. Details on the data construction and estimation procedure are provided in Appendix F.1.

Table 10 reports the estimates for the CES specification. Panel A of Table 10 presents the parameter estimates with standard errors, and Panel B of Table 10 reports Wald tests of the Cobb–Douglas restriction ($\rho = 0$, i.e., $\sigma = 1$) for each bundle.

The estimates deliver three main results. First, equipment capital and skilled labor are complements ($\hat{\sigma}_M = 0.716$), preserving the central message of Krusell et al. (2000) and Ohanian et al. (2023). In addition, the Cobb–Douglas restriction $\sigma_M = 1$ is rejected, confirming that the complementarity between equipment and skilled labor is significantly different from unitary elasticity. Second, structures and unskilled labor are substitutes ($\hat{\sigma}_S = 2.239$), indicating that the data do not support the implicit Cobb–Douglas treatment. Third, the outer elasticity governing substitution between the two bundles is $\hat{\sigma}_0 = 1.418$. The equality test further sharpens the picture. The two inner elasticities differ significantly, confirming that the equipment-skilled-labor and structures-unskilled-labor bun-

[34] Ohanian et al. (2023) normalize the structures price to one because structures enter as the Cobb-Douglas counterpart to the equipment-skilled labor CES composite and their prices are treated as being measured in the same numeraire units. In our modified specification, the additional structures-related parameter requires a separate structures-price series. The baseline uses the investment-based structures price constructed from BEA Fixed Assets Accounts Tables 2.7 and 2.8 and deflated by the GDP deflator, combined with the gross labor-share definition in Krusell et al. (2000) and Ohanian et al. (2023). For robustness, we also estimate the model using a stock-based structures price constructed from BEA Fixed Assets Accounts Tables 2.1 and 2.2, again deflated by the GDP deflator, and combine each price measure with both net and gross labor-share definitions.

Table 10: **Parameter Estimation Results**

Panel A. Parameter estimates

	$\hat{\rho}$	(SE)	$\hat{\sigma} = \frac{1}{1-\hat{\rho}}$
Outer (σ_0)	0.295	(0.013)	1.418
Equip–skilled (σ_M)	−0.396	(0.030)	0.716
Struct–unskilled (σ_S)	0.553	(0.060)	2.239
	Estimate	(SE)	
ω	0.570	(0.005)	
θ_M	0.245	(0.019)	
θ_S	0.579	(0.037)	

Panel B. Specification tests

H_0	Wald $\chi^2(1)$	p-value
$\sigma_0 = 1$	528.0	0.000
$\sigma_M = 1$	177.6	0.000
$\sigma_S = 1$	86.2	0.000
$\sigma_M = \sigma_S$	498.1	0.000

Notes. The table reports GMM estimation results using nonfarm business sector data with the investment-based structures price and the gross labor-share specification. Standard errors are reported in parentheses. $\sigma = 1/(1-\rho)$. Wald tests are $\chi^2(1)$. The first three test $\rho = 0$ ($\sigma = 1$), and the last test examines $\rho_M = \rho_S$.

dles exhibit distinct substitution patterns. Taken together, these results highlight a key departure from the Krusell et al. (2000) specification, which effectively treats structures as entering in Cobb–Douglas form with the rest of production.[35]

Although we impose a different functional form for aggregating inputs, the model delivers similar performance in matching the skill premium. We evaluate the model using the skill premium and the labor share as untargeted moments.

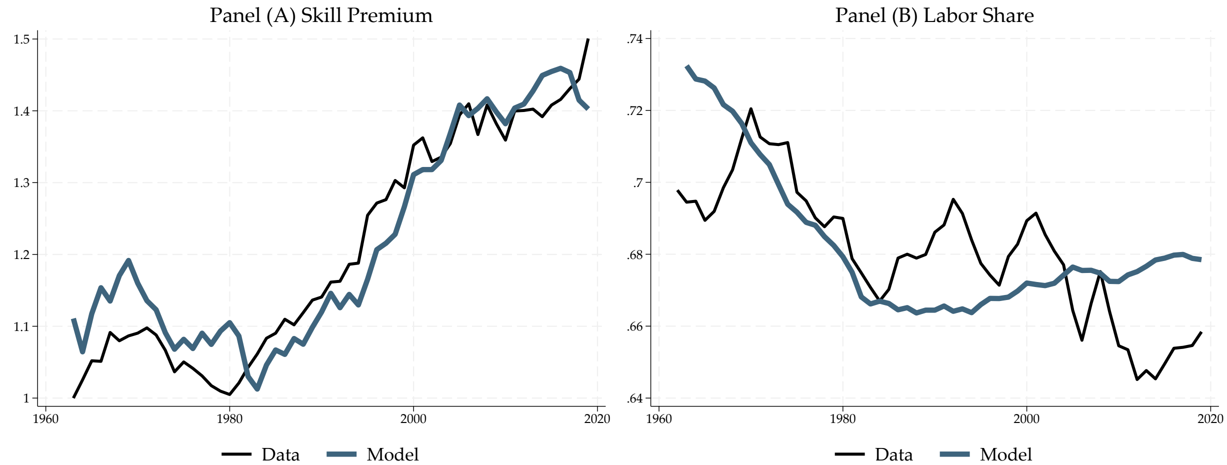
Figure 7 shows that the trend in the skill premium, which is not targeted in the calibration, closely matches the trend observed in the sample. By contrast, the labor share is well targeted until 1994, but the model does not capture its subsequent decline, sharing the limitation pointed out in Ohanian et al. (2023).

5.2 Structural Drag under CES Output Function

Having characterized the substitution patterns among inputs both within input bundles and across input bundles, we now turn to their implications for growth through structural drag. Under the CES output function, GDP per capita growth is given by the following

[35] The results are robust across alternative specifications, including gross and net labor-share measures and stock-based and investment-based structures-price series; see Appendix F.2 for details.

Figure 7: **Untargeted Moments**



Note. Panel A shows that the model-implied skill premium tracks the empirical trend. Panel B shows that the model does not reproduce the post-1994 labor-share decline, instead implying a stable or rising labor share.

analytical expression.[36]

$$g_{y,t} = \frac{n + \big((1-\phi)\mathbf{a}_{E,t} + \eta_E\big)\gamma_E + \big((1-\phi)\mathbf{a}_{S,t} + \eta_S\big)\gamma_S}{(1-\phi)(1-\mathbf{a}_{E,t}-\mathbf{a}_{S,t}) - (\eta_E+\eta_S)}, \tag{22}$$

The main difference from the Cobb–Douglas benchmark lies in the factor shares $\mathbf{a}_{E,t}$ and $\mathbf{a}_{S,t}$. Under Cobb–Douglas, these shares are fixed at the primitive values $\alpha_E \equiv \omega\theta_M$ and $\alpha_S \equiv (1-\omega)\theta_S$, so the coefficient associated with structures-price growth is as follows.[37]

$$D^{\text{CD}} = \frac{(1-\phi)\alpha_S + \eta_S}{(1-\phi)(1-\alpha_E-\alpha_S) - (\eta_E+\eta_S)}. \tag{23}$$

Under CES, by contrast, the factor shares $\mathbf{a}_{E,t}$ and $\mathbf{a}_{S,t}$ are endogenous objects that vary with the equilibrium allocation of quantities across the nested production structure. In

[36] To derive the expression in the main text, we close the following margins under the nested CES output function. The first two margins are the changes in equipment investment and structures investment relative to GDP. In addition, we close the reallocations of equipment, structures, and skilled labor between the output sector and the research sector. These assumptions are based on the empirical stability of capital investment shares relative to GDP, while the remaining assumptions are imposed because the data do not separately identify the output-sector and research-sector allocations of equipment, structures, and skilled labor. The derivation, along with the assumptions maintained throughout the analysis, is provided in Appendix F.3.

[37] Note that expression (23) is algebraically identical to the Cobb-Douglas structural-drag coefficient in equation (19). Let $\Psi \equiv 1-\alpha_E-\alpha_S$ and $\Delta \equiv (1-\phi)\Psi - (\eta_E+\eta_S)$. Then

$$\mathcal{M}_S = \frac{\alpha_S}{\Psi} + \frac{\eta_S(1-\alpha_E)+\eta_E\alpha_S}{\Psi\Delta} = \frac{\alpha_S\Delta + \eta_S(1-\alpha_E)+\eta_E\alpha_S}{\Psi\Delta} = \frac{(1-\phi)\alpha_S+\eta_S}{\Delta} \equiv D^{\text{CD}}.$$

particular, the corresponding output-level shares are

$$\mathbf{a}_{E,t} = s_{M,t} s_{K_E|M,t}, \qquad \mathbf{a}_{S,t} = (1 - s_{M,t}) s_{K_S|S,t}. \tag{24}$$

where

$$s_{K_E|M,t} = \frac{\theta_M K_{E,t}^{\rho_M}}{\theta_M K_{E,t}^{\rho_M} + (1-\theta_M) L_{s,t}^{\rho_M}}, \quad s_{K_S|S,t} = \frac{\theta_S K_{S,t}^{\rho_S}}{\theta_S K_{S,t}^{\rho_S} + (1-\theta_S) L_{u,t}^{\rho_S}}, \quad s_{M,t} = \frac{\omega M_t^{\rho_0}}{\omega M_t^{\rho_0} + (1-\omega) S_t^{\rho_0}}.$$

In words, the equipment share in output $\mathbf{a}_{E,t}$ is given by the top-nest share of the M-bundle multiplied by the within-M-bundle share of equipment, while the structures share in output $\mathbf{a}_{S,t}$ is given by the top-nest share of the S-bundle, $1 - s_{M,t}$, multiplied by the within-S-bundle share of structures. This decomposition makes clear that output-level shares are shaped by both between-bundle allocation and within-bundle composition.

Because these shares are endogenous, the effect of structures-price growth is not exhausted by a single term as in the Cobb–Douglas case. Differentiating (22) with respect to γ_S yields the total effect of structures-price growth:

$$\frac{\mathrm{d}g_{y,t}}{\mathrm{d}\gamma_S} = \left.\frac{\partial g_{y,t}}{\partial \gamma_S}\right|_{\mathbf{a}} + \frac{\partial g_{y,t}}{\partial \mathbf{a}_{E,t}} \frac{\mathrm{d}\mathbf{a}_{E,t}}{\mathrm{d}\gamma_S} + \frac{\partial g_{y,t}}{\partial \mathbf{a}_{S,t}} \frac{\mathrm{d}\mathbf{a}_{S,t}}{\mathrm{d}\gamma_S}. \tag{25}$$

The first term is the direct effect:

$$\left.\frac{\partial g_{y,t}}{\partial \gamma_S}\right|_{\mathbf{a}} = \frac{(1-\phi)\mathbf{a}_{S,t} + \eta_S}{(1-\phi)(1 - \mathbf{a}_{E,t} - \mathbf{a}_{S,t}) - (\eta_E + \eta_S)}, \tag{26}$$

which is the nested-CES counterpart to the structural drag term in the Cobb–Douglas case, evaluated at the current endogenous shares. The remaining terms capture the additional channels that arise because structural ISTC γ_S also changes the output shares themselves. Under the CES structure, the response of the equipment share, the second term in the decomposition in equation (25), is given by

$$\frac{\mathrm{d}\mathbf{a}_{E,t}}{\mathrm{d}\gamma_S} = (\sigma_0 - 1)\mathbf{a}_{E,t}(1 - s_{M,t}) s_{K_S|S,t} \mu_S, \qquad \mu_S \equiv \frac{1}{r + \delta_S + \gamma_S} \tag{27}$$

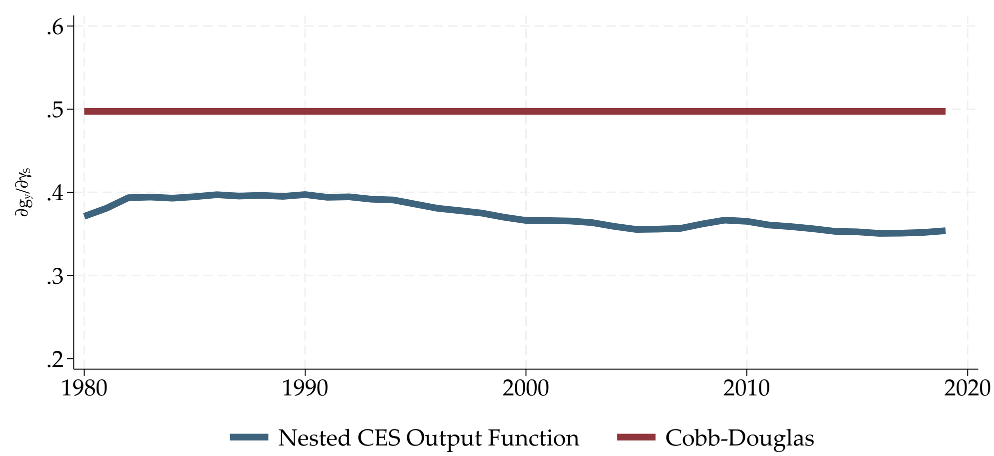
whereas the response of the structures share can be decomposed into two components

$$\frac{\mathrm{d}\mathbf{a}_{S,t}}{\mathrm{d}\gamma_S} = -(\sigma_0 - 1) s_{M,t}(1 - s_{M,t}) s_{K_S|S,t}^2 \mu_S - (\sigma_S - 1)(1 - s_{M,t}) s_{K_S|S,t}(1 - s_{K_S|S,t}) \mu_S. \tag{28}$$

Equations (27) and (28) show that the indirect effect of structures-price growth operates through three distinct margins: an outer-nest reallocation effect through $\mathbf{a}_{E,t}$, an outer-nest reallocation effect through $\mathbf{a}_{S,t}$, and a within-S substitution effect through $\mathbf{a}_{S,t}$. Thus, under CES, structural drag is shaped not only by the direct loading term in (26), but also by the endogenous adjustment of output shares induced by changes in structures-price growth.

Based on the estimated CES parameters in Table 10, the model predicts that structural drag *declines* over time as rising structures costs induce substitution away from structures-intensive margins. First, since $\sigma_0 > 1$, the top nest is sufficiently substitutable that an increase in structures-price growth raises the user cost of structures and induces reallocation away from the structures-intensive bundle and toward the M-bundle. Second, since $\sigma_S > 1$, the within-S nest is also substitutable, so the share of structures within that bundle declines as well. These two margins work in the same direction, implying a downward trend in $\mathbf{a}_{S,t}$ and, in turn, a weakening of the structural-drag force. Finally, the outer-nest reallocation raises $\mathbf{a}_{E,t}$, but only modestly: because equipment and skilled labor are complements within the M-nest ($\sigma_M < 1$), the within-bundle composition cannot adjust freely, dampening the rise in $\mathbf{a}_{E,t}$.

Figure 8: **Structural Drag Comparison, Cobb-Douglas vs. CES**



Notes. The figure compares the model-implied structural drag under different output technologies. The red line plots the implied structural drag under the Cobb–Douglas specification based on the baseline calibration, while the blue line shows the time-varying structural drag implied by the CES production function in equation (25). For the CES case, we compute the model-implied series using the capital-stock and labor-hours data from Ohanian et al. (2023).

Figure 8 shows that this prediction is borne out quantitatively when the estimated CES structure is evaluated using the data. Relative to the Cobb–Douglas benchmark, where the drag is fixed at approximately 0.5, the CES specification delivers a smaller drag that also declines over time. In the data, the CES-based drag starts at around 0.4 and falls to below 0.35 in recent periods.

Thus, the main implication of moving beyond Cobb–Douglas is not that structural drag disappears, but that its magnitude is lower and continues to decline as the economy endogenously adjusts its input mix. Under the CES extension, negative structures ISTC still exerts a drag on GDP per capita growth, but its quantitative effect becomes smaller because endogenous share adjustment allows the economy to reallocate away from structures-intensive production margins as relative prices change. In particular, substitution both across bundles and within the structures–unskilled-labor bundle reduces the output share of structures over time, thereby weakening the growth impact of adverse structures ISTC.

5.3 How Do Structures Affect the Skill Premium?

The extended CES specification also allows us to analyze how the presence of structures, together with their rising relative price, affects the skill premium, a question that the Cobb–Douglas specification cannot address.[38]

Following Krusell et al. (2000), the growth rate of the skill premium can be decomposed as follows:[39]

$$g_\pi = \frac{1}{\sigma_0}\left(g_{L_u} - g_{L_s}\right) + \left(\frac{1}{\sigma_M} - \frac{1}{\sigma_0}\right) s_{K_E|M}\left(g_{K_E} - g_{L_s}\right) - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_0}\right) s_{K_S|S}\left(g_{K_S} - g_{L_u}\right). \tag{29}$$

Equation (29) decomposes skill-premium growth into three components: a relative labor-supply term, an equipment–skilled-labor complementarity term in the spirit of Krusell et al. (2000), and a structures-unskilled-labor term that captures the role of structures under the estimated CES technology.

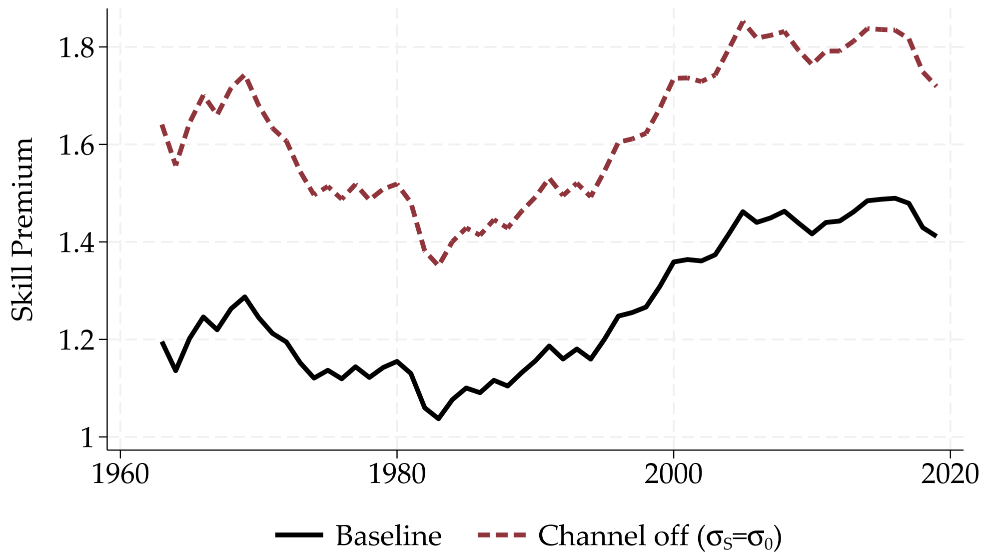
As shown above, structures and unskilled labor are substitutes, suggesting that a decline in structures ISTC reduces the skill premium by shifting demand away from structures and toward unskilled labor. To quantify this channel, we follow the counterfactual exercise in Krusell et al. (2000) and impose that the elasticity of substitution between structures and unskilled labor is equal to the elasticity governing substitution between the M- and S-bundles. This exercise isolates the quantitative role of the structures–unskilled labor margin without changing the broader CES environment. By imposing $\sigma_0 = \sigma_S$, the specification removes the additional structure-specific substitution term in the skill-

[38]Our framework differs from the existing literature in an important respect. Whereas previous studies typically assume a Cobb–Douglas aggregation of structures, a CES bundle of equipment capital and skilled labor, and unskilled labor (Krusell et al., 2000), we instead adopt the CES production structure in (20) and use the estimated substitutability parameters for each margin.

[39]See Appendix F.4 for the derivation.

premium decomposition, so the difference relative to the baseline can be attributed to that channel alone. The rest of the model, including the production structure, the other parameters, and the equilibrium framework, remains unchanged, which makes the comparison internally consistent.

Figure 9: **Counterfactual Skill Premium**



Notes. The figure plots the actual skill premium in black and the counterfactual skill premium in red under the restriction $\sigma_0 = \sigma_S$ from 1963 to 2019. The model-implied series is computed using capital-stock and labor-hours data from Ohanian et al. (2023).

Figure 9 shows that the counterfactual skill premium is consistently higher than the baseline path once the structures-unskilled-labor margin is shut down by imposing $\sigma_0 = \sigma_S$. The intuition is straightforward. When structures and unskilled labor are allowed to substitute within their own bundle, the rising relative price of structures induces firms to lean more heavily on unskilled labor as a partial replacement. This raises the relative demand for unskilled workers and compresses the skilled–unskilled wage gap. Once the margin is removed and structures are forced to substitute with the rest of production only through the outer nest, this offsetting force disappears, and the skill premium rises more strongly over time.

Quantitatively, the gap between the two series is economically meaningful. Over 1963–2019, the counterfactual path implies a cumulative rise in the skill premium that is approximately 30% larger than in the baseline. This magnitude carries a direct implication for the canonical capital–skill complementarity framework of Krusell et al. (2000), which embeds structures as a Cobb–Douglas factor separable from the skill-complementary capital stock and therefore rules out this channel by construction. In that specification, the entire rise in the skill premium attributable to capital must be loaded onto the equipment–skilled-labor margin. Our estimates suggest that doing so overstates the role of capital–skill complementarity, because part of what would be assigned to equipment is in fact offset by structures–unskilled-labor substitution. The structures channel is thus not only a force shaping aggregate growth, as emphasized in Section 5.2, but also a previously unrecognized determinant of measured wage inequality.

6 Concluding Remarks

This paper challenges the view that investment-specific technological change in equipment is a sufficient statistic for long-run growth. Disaggregating capital into equipment and structures reveals a fundamental tension: falling equipment prices have lowered the cost of producing both output and ideas, but rising structures prices have simultaneously imposed a binding constraint on capital accumulation and innovation. In our calibrated model, structural drag offsets roughly 38% of the equipment boost, with about three-quarters of the drag operating through reduced capital deepening and the remainder through R&D-related channels.

Allowing for substitution among inputs reinforces and refines these conclusions. Structures and unskilled labor are substitutes within their bundle, and this bundle is in turn a substitute for the equipment–skilled-labor bundle, while equipment and skilled labor remain complements. These margins shrink the drag by 20-30% and, more importantly, reveal a previously unrecognized channel through which structures prices shape wage inequality. Because structures and unskilled labor are substitutes, the rising relative price of structures raises the relative demand for unskilled labor and dampens the rise in the skill premium. Ignoring this channel overstates the 1963–2019 rise in the U.S. skill premium by 30%.

These findings carry implications for both growth policy and the study of inequality. Efforts to accelerate technological progress in equipment-producing industries may yield diminishing returns if not accompanied by policies addressing productivity stagnation in construction. Why structures productivity has followed what Goolsbee and Syverson (2023) call a "strange and awful path" remains a critical open question. Our framework provides a lens through which to evaluate the aggregate implications of any improvement in construction productivity, and points to a previously unrecognized link between construction-sector stagnation and the skilled–unskilled wage gap, suggesting that its consequences extend well beyond aggregate output.

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ONLINE APPENDIX

A Details on Capital Price and Expenditure Measurement

Our primary analysis examines how heterogeneity in capital relates to development outcomes using three main data sources. For international price and capital measures, we use the International Comparison Program (ICP) and the Penn World Table (PWT) version 11.0, especially the Capital Detail module. For the research and development (R&D) sector, we use the National Center for Science and Engineering Statistics (NCSES) Business Enterprise Research and Development (BERD) survey for U.S. data, complemented by gross domestic expenditure on R&D (GERD) for cross-country comparisons.

We use the PWT Capital Detail data to characterize time-series trends in capital prices, with a focus on equipment and structures. We use ICP price data primarily for cross-sectional regressions that relate asset-type price levels to GDP per capita. We use BERD to measure and decompose R&D-related capital expenditures by asset type, and we use GERD for robustness checks. This section clarifies the interpretation of each variable and describes data coverage.

A.1 The International Comparison Program

We focus on ICP price measures for two capital categories, Machine and Equipment (item 1501100) and Structures (item 1501200). In the ICP classification, these categories correspond to expenditure items under gross fixed capital formation.

Machine and Equipment. This category corresponds to Machinery and Equipment (1501100) under Gross Fixed Capital Formation (1501000). It covers Metal products and equipment (1501110), Fabricated metal products (1501111), Electrical and optical equipment (1501112), General purpose equipment (1501115), Special purpose equipment (1501116), and Transport equipment (1501120).

Structures. This category corresponds to Structures (1501200) under Gross Fixed Capital Formation (1501000). It covers Residential buildings (1501210), Non-residential buildings (1501220), and Civil engineering works (1501230).

Other ICP capital formation components. In addition to Machine and Equipment (1501100) and Structures (1501200), the ICP capital formation block includes Other Products (1501300) within Gross Fixed Capital Formation (1501000), Changes in Inventories (1502000) within Gross Capital Formation (1500000), and Acquisitions Less Disposals of Valuables (1503000) within Gross Capital Formation (1500000). We report these categories for completeness.

A.2 Penn World Table Capital Detail

PWT capital measures, including capital services and relative prices of capital, are constructed from investment data by asset.[40] 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** includes computers, communication equipment, and other equipment. **Structures** include residential and non-residential structures. **Transport equipment** is reported as a separate asset group. **Other assets** include software, other intellectual property products, and cultivated assets.

A.3 U.S. Bureau of Economic Analysis Fixed Assets / Industry Accounts

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

Asset categories. The BEA asset classification[41] allows us to distinguish between equipment and structures. We define equipment as information-processing equipment, industrial equipment, transportation equipment, and other equipment assets.[42] We define structures as residential and nonresidential structures, together with associated nonbuilding structures.[43] The post-1990 increase in relative structures prices documented in the

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

[41] 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

[42] BEA capitalization guidance treats an item as equipment if it has a useful life of more than 1 year, is not an integral part of a structure and is not included in the value of that structure, and would normally be charged to a capital account in business accounting records.

[43] BEA includes in structures the structures of new nonresidential and residential buildings, improvements to buildings, and certain types of equipment that are considered an integral part of the structure. It also includes nonbuilding structures, mobile structures, manufactured homes, well drilling and exploration, mine development, brokers' commissions and ownership transfer costs, and net purchases of existing structures from governments.

main text is broad based across these subcategories rather than driven by a single component.

BEA Fixed Assets Accounts. Based on the above definitions, 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.

For investment in private fixed assets by asset type, we use BEA Fixed Assets Accounts 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 convert the chain-type quantity index into a real investment series using the corresponding base-year nominal value, and then construct an implicit investment price index as nominal investment divided by real investment. For capital stocks by asset type, we 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, to verify that the observed investment price dynamics extend to the capital stock itself.

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. 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.

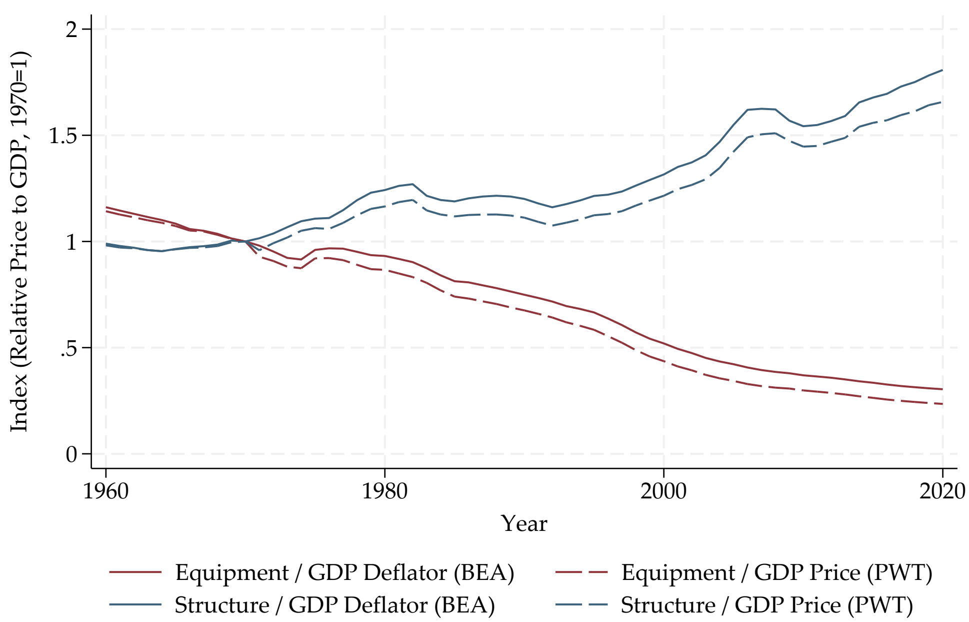
As an alternative measure of exposure, we compute the structures share in the capital stock using Table 3.1ESI, Current-Cost Net Stock of Private Fixed Assets, Equipment, Software, and Intellectual Property Products by Industry, and Table 3.1S, Current-Cost Net Stock of Private Structures by Industry. 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. 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 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, construction, 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.

Comparison with Penn World Table Capital. To ensure that the BEA and PWT Capital Detail exhibit consistent trends, we compare the relative prices of equipment and structures across the two sources, where relative prices are measured relative to the GDP price.

Figure A.1: **Relative Price Trend of Two Asset Types Investment from BEA and PWT**



Notes. The figure compares U.S. asset price indices for equipment and structures constructed from the BEA and the PWT Capital Detail over 1960–2020, with all series normalized to 1970=1. For the BEA series, an asset-type price index is constructed as the ratio of nominal investment to real investment, where real investment is obtained by converting the BEA quantity index, 2017=100, using the 2017-dollar level. The BEA relative price is computed by dividing the normalized asset price index by the GDP deflator, GDPDEF. For the PWT series, asset price indices for machinery and equipment and structures are normalized to 1970=1. The GDP price in national accounts is computed as $p_{gdp} = v_{gdp}/q_{gdp}$, normalized to 1970=1, and the PWT relative price is defined as the normalized asset price index divided by the normalized p_{gdp}. Solid lines denote BEA series and long-dashed lines denote PWT series. Equipment and structures are distinguished by color as indicated in the legend. *Sources.* Bureau of Economic Analysis, Fixed Assets, Penn World Table 11.0, PWT Capital Detail, and authors' calculations.

Figure A.1 compares the U.S. relative prices of equipment and structures from the BEA and the PWT Capital Detail over 1960–2020. For the BEA, we normalize the price indexes for these two asset types by the GDP deflator. For the PWT Capital Detail, we normalize the corresponding price indexes by the GDP price in the national accounts, constructed by dividing nominal GDP in local currency units by real GDP.

BEA asset composition of asset-class investment and relative prices. Table A.I reports, for the year 2020, how total investment in each asset class is allocated across detailed BEA asset categories within the broad groups of equipment and structures. The table also reports relative prices in 2020, where each asset's real price in 1970 is normalized to 1.

Table A.I: **Investment Shares by BEA Asset Category and Relative Prices in 2020**

Asset Class	**Share**	**Price**	**Asset Class**	**Share**	**Price**
Equipment	100%	0.304	Structures	100%	1.808
Communication Equipment	10.961%	0.056	Housing (1 To 4 Unit)	21.473%	1.719
Computers And Peripheral Equipment	10.916%	<0.001	Improvements	19.777%	1.545
Medical Equipment And Instruments	9.573%	0.426	Brokers' Commission	12.897%	1.866
Light Trucks	9.447%	0.763	Office	6.173%	1.907
General Industrial Machinery	8.257%	1.062	Electric	5.661%	1.715
Other Nonresidential Equipment	6.454%	0.765	Housing (5 Or More)	5.540%	2.135
Electrical Transmissions	4.273%	0.760	Manufacturing	5.001%	1.735
Furniture And Fixtures	4.092%	1.008	Petroleum And Natural Gas	3.972%	4.399
Other Trucks, Buses, And Truck Trailers	3.795%	1.206	Warehouses	2.854%	1.869
Special Industry Machinery	3.786%	1.219	Lodging	2.282%	1.769
Aircraft	3.597%	1.524	Communication	1.595%	0.929
Nonmedical Instruments	3.074%	0.795	Hospitals	1.535%	1.524
Construction Machinery	3.065%	1.368	Other Power	1.488%	2.042
Agricultural Machinery	2.948%	1.306	Educational And Vocational	1.205%	2.020
Service Industry Machinery	2.875%	0.857	Amusement And Recreation	1.097%	1.682
Metalworking Machinery	2.794%	1.045	Medical Buildings	1.010%	1.526
Mining And Oilfield Machinery	2.299%	1.549	Other Commercial	0.996%	1.729
Fabricated Metal Products	1.803%	1.117	Manufactured Homes	0.841%	1.324
Residential Equipment	1.550%	0.279	Land	0.761%	1.333
Engines And Turbines	0.874%	1.094	Multimerchandise Shopping	0.734%	1.768
Electrical Equipment	0.820%	0.655	Mining	0.606%	1.797
Railroad Equipment	0.703%	1.203	Food And Beverage Establishments	0.592%	1.830
Photocopy And Related Equipment	0.658%	0.228	Farm	0.565%	1.753
Ships And Boats	0.550%	1.252	Special Care	0.411%	1.532
Autos	0.451%	0.502	Air	0.303%	1.685
Office And Accounting Equipment	0.388%	0.289	Other Residential	0.289%	2.021
			Religious	0.236%	1.866
			Other	0.121%	1.516

Notes: **Share** denotes each detailed BEA asset category's share of total 2020 investment within the corresponding asset type, Equipment or Structures. **Price** is the ratio of the asset's real price in 2020 to its real price in 1970, where real prices are nominal prices deflated by the GDP deflator and the 1970 level is normalized to 1. Within each broad group, categories are ordered in descending order of Share.

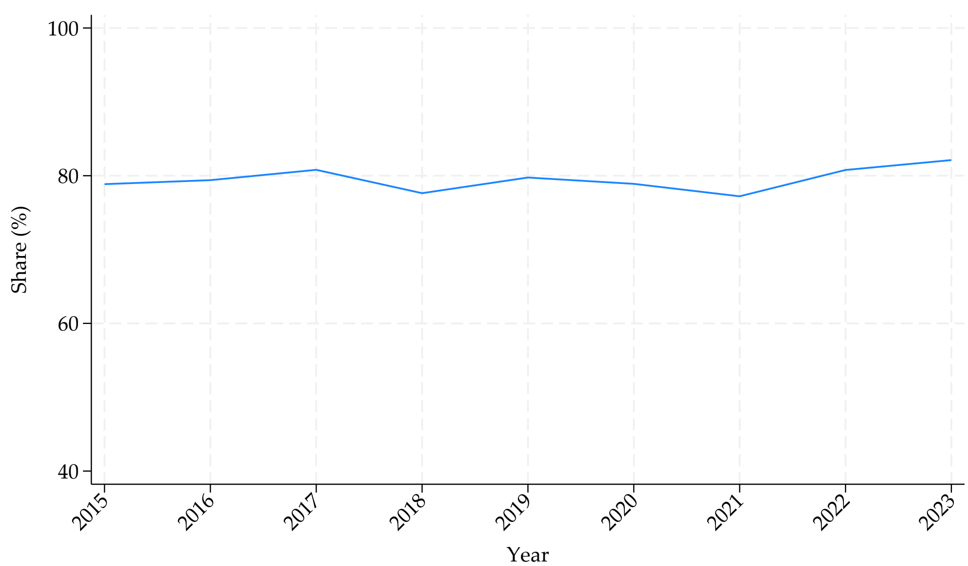
A.4 NCSES Business Enterprise Research and Development BERD Capital Expenditures Classification

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.[44]

For the 2015 BERD survey instrument, the relevant items request domestic capital expenditures for R&D operations in Question 2.32 and a required breakdown of those domestic R&D capital expenditures in Question 2.33. The categories are Structures, Equipment, Capitalized software, and All other expenditures. Structures include the costs of purchased or improved buildings and other facilities such as signal towers or windmills that are fixed to the land. All other expenditures include the costs of purchased patents or other intangible assets.[45] 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.

Figure A.2: **Equipment Investment Share in R&D Sector in the U.S.**



Notes. The figure shows a time series of equipment investment as a share of the sum of equipment and structures investment. The time series is constructed using total expenditures across all industries. *Sources.* BERD and authors' calculations.

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

Figure A.2 plots a time series of equipment investment as a share of total investment in equipment and structures. The series is constructed using total expenditures across all industries. Since 2015, the share has remained stable at around 80%.

A.5 Gross Domestic Expenditure on R&D (GERD)

Gross domestic expenditure on research and development (GERD) measures the total intramural spending on R&D performed within a country during a given reference year. GERD is constructed as the aggregate of R&D expenditures reported by all performing sectors under the OECD reporting framework, which distinguishes both performing sectors and sources of funds. In this paper, we focus on the business enterprise performing sector and exclude government, higher education, private nonprofit, and foreign-funded performing sectors from our baseline construction.

Capital types are classified based on The Frascati Manual.[46] We use two capital expenditure categories. Land and Buildings include land acquired for R&D use, such as testing grounds and sites for laboratories or pilot plants, and buildings constructed or purchased for R&D use, including major improvements, modifications, and repairs. This corresponds to Sections 4.48 to 4.50. Machinery and equipment include major capitalized machinery and equipment acquired for use in the performance of R&D. This corresponds to Section 4.51.

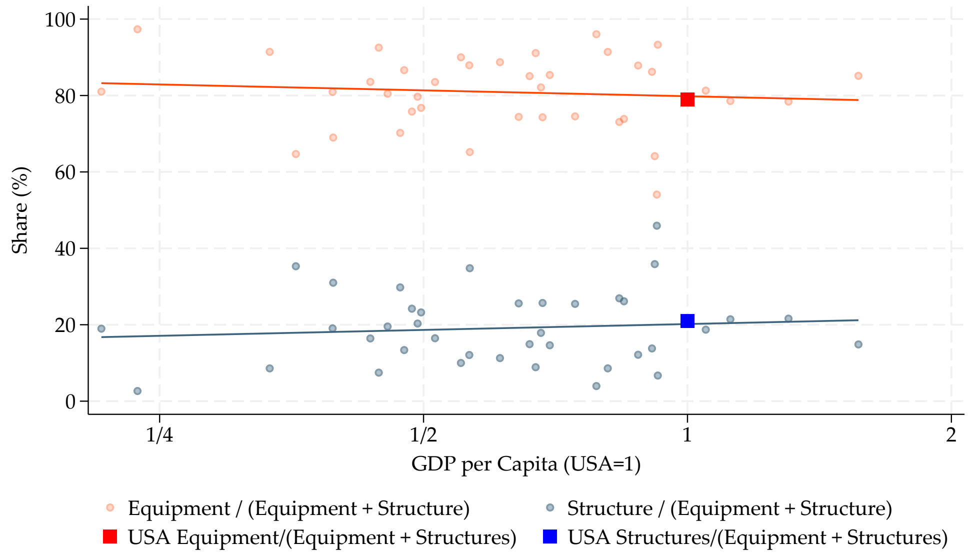
A practical issue for empirical work is that land and buildings are frequently reported jointly, and separate identification of land is not consistently available. While land is conceptually part of the land and buildings category, when the category is reported as a single total, the reported value is typically dominated by buildings and related construction and improvements rather than land acquisition. For this reason, we use land and buildings as the structures measure.

We calculate the allocation of capital expenditures between equipment, measured as machinery and equipment, and structures, measured as land and buildings, using GERD data for 45 countries based on 2014 to 2019 averages. We then compare these patterns with U.S. evidence from BERD, yielding a total sample of 46 countries.

Figure A.3 plots the structures share and the equipment share in total equipment-plus-structures investment against relative GDP per capita in 2017, normalized to one for the United States. Across the income distribution, the equipment share in R&D capital expenditure is close to 80%, consistent with the 79% estimate for the United States from BERD.

[46] https://www.oecd.org/content/dam/oecd/en/publications/reports/2015/10/frascati-manual-2015_g1g57dcb/9789264239012-en.pdf

Figure A.3: **Equipment and Structures Investment Allocation in R&D Sector**



Notes. The orange series reports the equipment share and the blue series reports the residual share, namely the structures share. For countries other than the United States, we use GERD and define the equipment share as machinery and equipment divided by land and buildings plus machinery and equipment, with the structures share defined as land and buildings divided by land and buildings plus machinery and equipment. For the United States, we use BERD and define the equipment share as equipment divided by structures plus equipment, with the structures share defined as structures divided by structures plus equipment. GDP per capita in PPP terms on the horizontal axis is expressed relative to the United States, so that the U.S. equals one. *Sources.* BERD, GERD, PWT 11.0, and authors' calculations.

Correspondingly, the structures share is close to 20%. Overall, these results indicate that the equipment intensity of R&D capital spending is broadly stable across countries.

A.6 EU KLEMS Database

The EU KLEMS database provides harmonized growth and productivity accounts for major countries, including the U.S. It offers detailed industry-level data within a consistent accounting framework across countries. In this paper, we use the 2024 vintage, which starts in 1996. From the national accounts module, we draw gross output at current prices (`GO_CP`), intermediate inputs (`II_CP`), value added (`VA_CP`), labor compensation (`COMP`), and the corresponding price indexes (`GO_PI`, `II_PI`, and `VA_PI`) for each NACE/ISIC sector. From the growth accounts module, we use quantity indexes for labor input (`LAB_QI`) and capital services (`CAP_QI`). We compute nominal labor compensation as `COMP` and nominal capital compensation as `VA_CP-COMP`, and derive implicit factor price indexes by dividing each nominal compensation measure by the corresponding quantity index. These variables allow us to construct industry-level cost shares and input price changes for each country-year, which constitute the building blocks of the dual price decomposition.

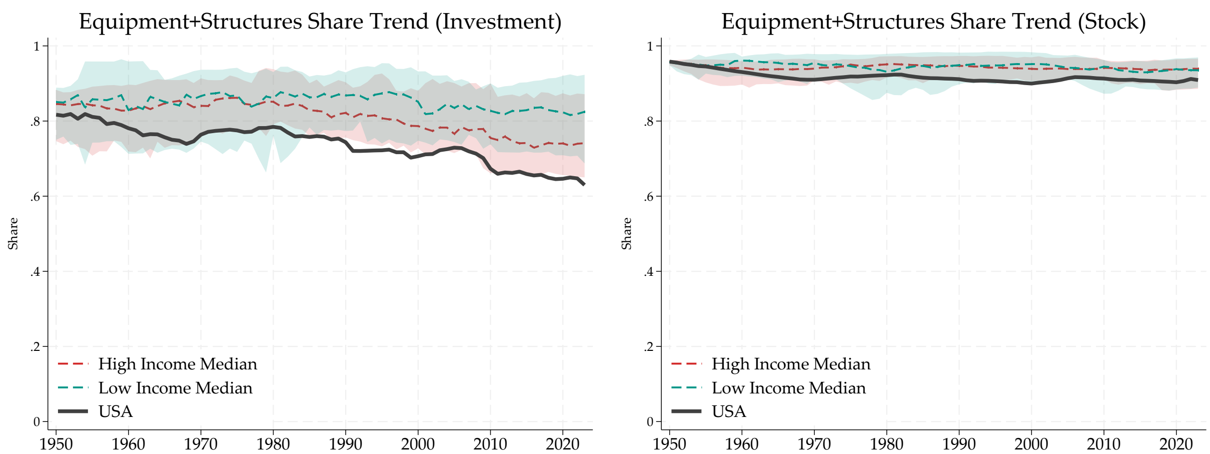
B Robustness Checks on Stylized Facts

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 Structures and Equipment in Total Investment**

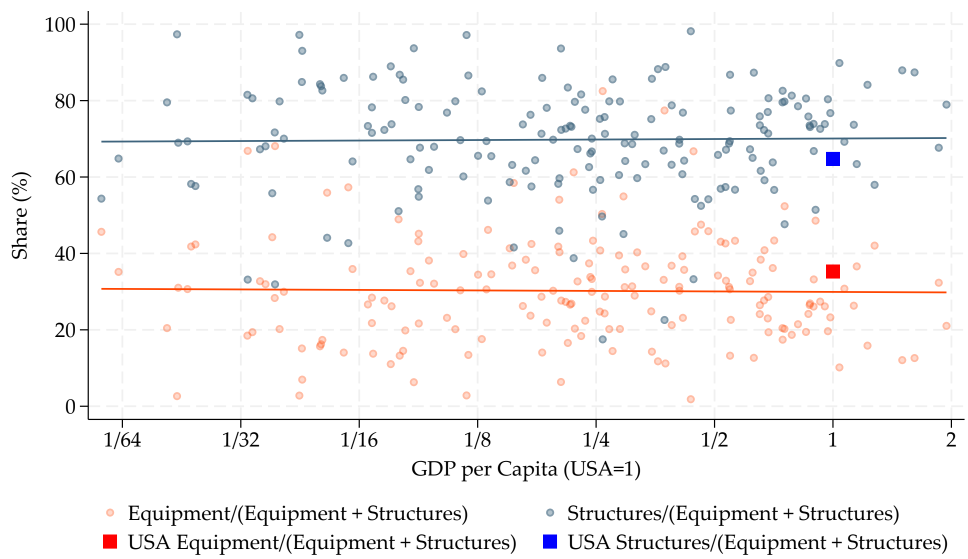


Notes. The figure plots time series of investment shares constructed from Penn World Table capital-detail categories. The share is computed as the ratio of a component to the sum of four components: Structures, Machinery and Equipment, Transport Equipment, and Other assets. The left panel is based on investment (*Ic*) and the right panel is measured based on capital 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. *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.

Additionally, we plot how the equipment and structures investment shares vary across countries. Figure B.2 plots, for 2021, each country's equipment and structures shares of total investment against relative GDP per capita (USA = 1), with the United States highlighted and fitted trend lines shown.

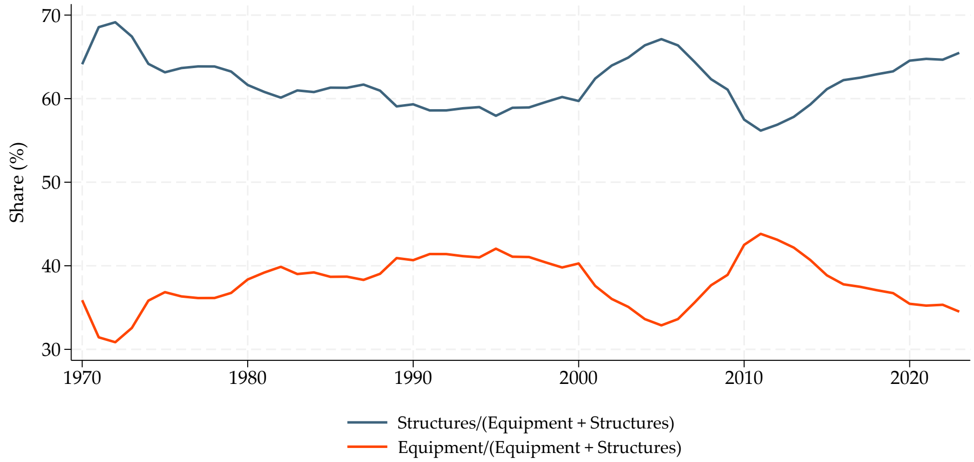
Figure B.2: **Equipment and Structures Investment Allocation**



Notes: The figure plots, for 2021, each country's investment allocation between equipment and structures against relative GDP per capita (USA=1). Circles show country observations; the U.S. observation is highlighted. Solid lines are separate linear fits of the equipment share and the structures share on relative GDP per capita. The equipment share is defined as $E/(E+S)$ and the structures share as $S/(E+S)$, where E and S correspond to equipment and structures components of investment, respectively. GDP per capita (in PPP terms) is expressed relative to the United States so that the U.S. equals one. *Source*: PWT 11.0 Capital Detail

Finally, we plot the time series for the share of equipment investment in total investment in equipment and structures in Figure B.3. This series is used to calibrate the model parameter that pins down the output share of equipment relative to structures. As the figure shows, the equipment share increased by roughly 5 percentage points from the 1970s to the 1980s and remained broadly stable for the subsequent two decades. The series displays a transitory fluctuation around the 2008 Great Financial Crisis, with a mean of approximately 40%.

Figure B.3: **Equipment and Structures Investment Allocation Time Series in the U.S.**



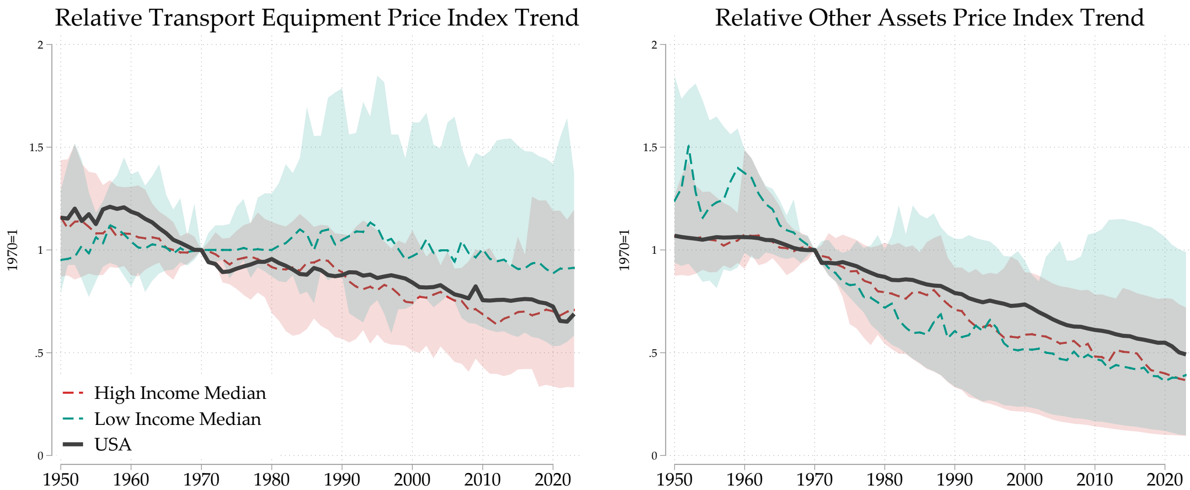
Notes: The figure plots the allocation of investment between equipment and structures in the United States from 1970 to 2024. The equipment share is defined as $E/(E+S)$ and the structures share as $S/(E+S)$, where E and S denote the equipment and structures components of investment, respectively. *Source*: PWT 11.0 Capital Detail

B.1.2 Relative Price Trend of Other Capital Asset Types

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.4 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.

Figure B.4: **Relative Investment Price Index Trend of Other Capital Assets**



Notes. The relative price for each asset type is calculated by dividing each asset type'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. *Sources.* Penn World Table 11.0, PWT Capital Detail, and authors' calculations.

B.1.3 Relative Price Trends Based on Capital Stocks

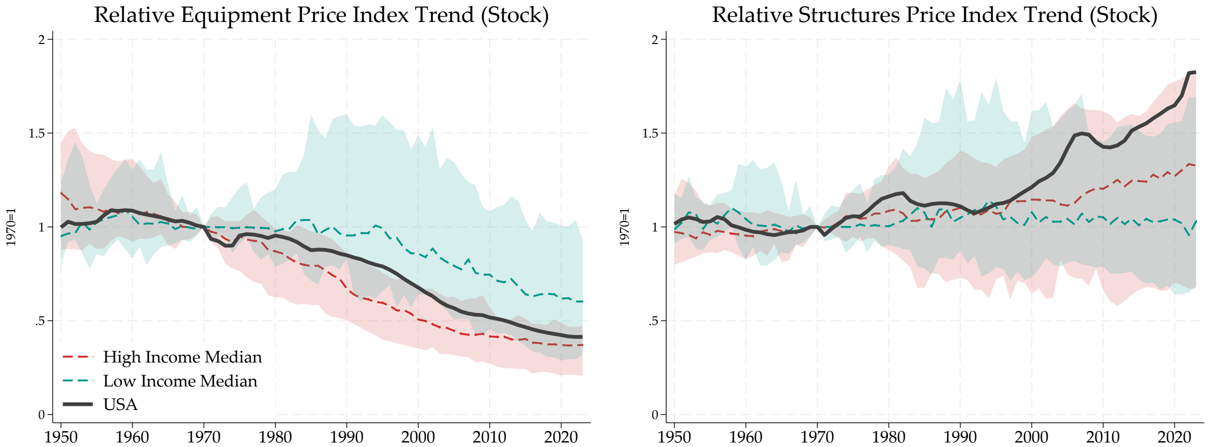
PWT provides price indices for capital based on capital stocks (Capital Stock Price Indices; series codes begin with `Np`). The stylized facts we report for other capital-asset trends remain unchanged when we use these stock-based price indices. Figure B.5 shows that equipment prices decline more rapidly 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.

B.1.4 Price Trends from ICP

We construct ICP-based cross-country relative prices, 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.5: **Relative Capital Stock Price Index Trend**



Notes. The relative price for each asset type 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. *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 $k \in \{\text{equipment}, \text{structures}\}$ 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

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

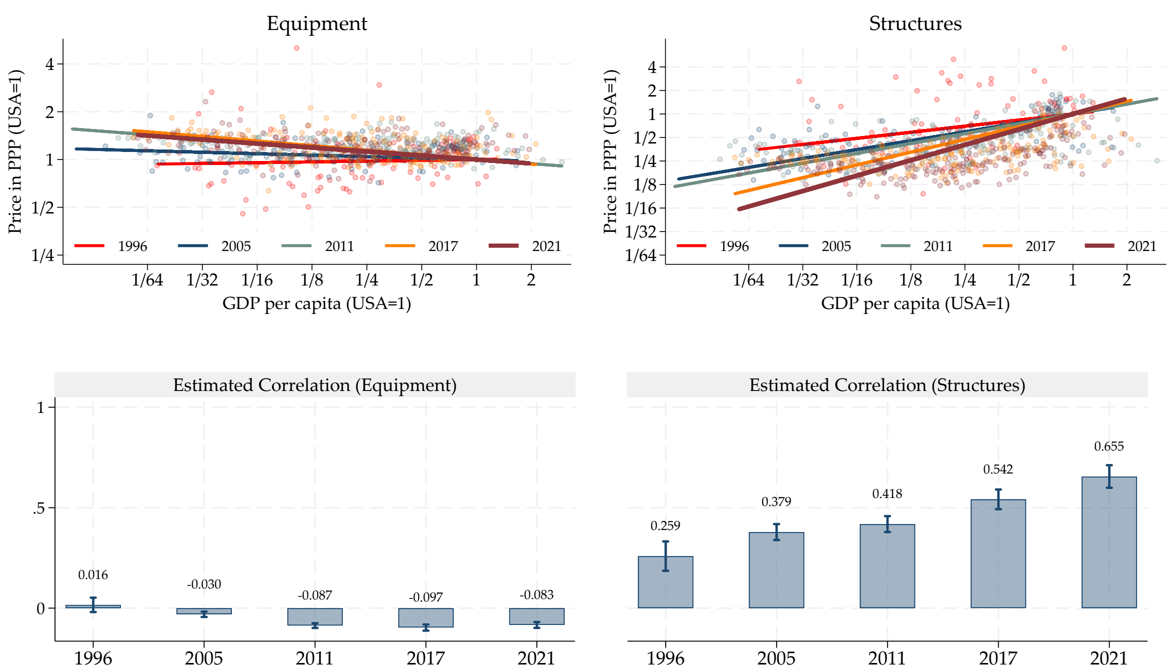
For visualization, we plot U.S.-normalized relative levels, obtained by exponentiating the log ratios above. Thus, the United States equals one in each survey year, and values such as 1/2 and 2 indicate prices or incomes one half or twice the U.S. level. In addition, for each survey year t, we estimate 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.6 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 prices and income in later survey waves. The bottom row summarizes the corresponding year-by-year regression slopes and their 95% confidence intervals.

Figure B.6: **ICP cross-country relative prices and income gradients by survey year**

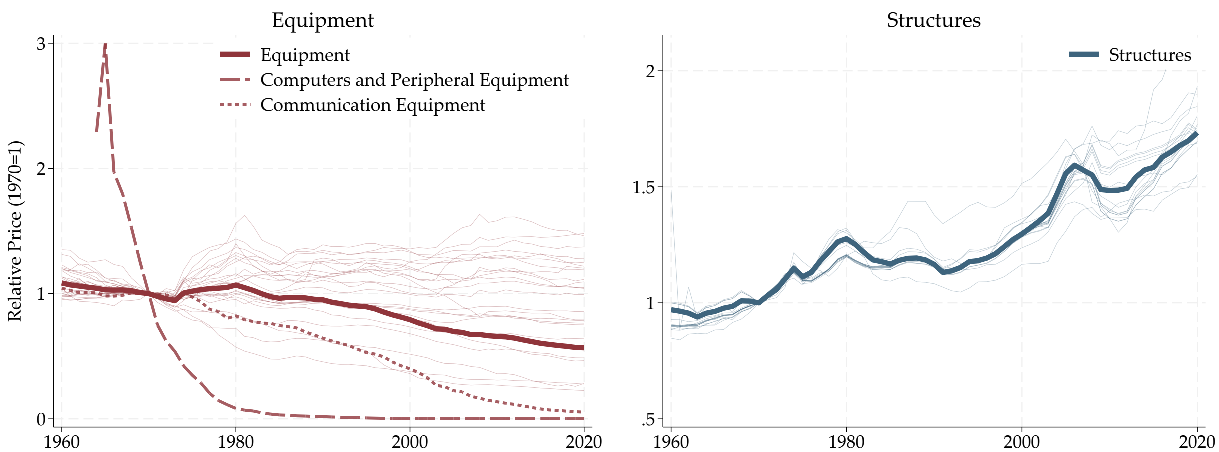


Notes: Each dot is a country. Both axes report U.S.-normalized relative levels. The United States equals one in each survey year. The underlying regressions use log ratios relative to the United States. The fitted lines in the top row are survey-year-specific cross-sectional regressions with no intercept. The bottom row reports the estimated slopes and 95% confidence intervals for equipment and structures by survey year.

B.2 Additional results on Fact 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.7 plots relative net capital stock price indices by BEA asset type over the period 1960–2020. The stock-price patterns closely mirror those of the investment price indices. For each asset category, we recover an implicit net-stock price index from current-cost net capital stock values and the corresponding chain-type quantity indexes. We then express each index relative to the GDP deflator and normalize it to unity in 1970.

Figure B.7: **Relative Net Stock Price Index Trend by Asset Type (1960-2020)**



Notes: The figure plots trends in relative net capital stock prices by BEA asset type. For each asset type, 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 GDP Deflator 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; Gross Domestic Product: Implicit Price Deflator (GDPDEF) from Federal Reserve Bank of St. Louis (FRED); and authors' calculations.

The resulting trends closely mirror those for investment prices. Equipment prices fall sharply after 1970, driven primarily by information-processing assets such as computers and peripheral equipment and communication equipment, while structures prices 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 Robustness Checks on Construction Sector Productivity

This section uses Törnqvist decompositions, following Diewert (1976), to show that rising structures prices are closely related to weak productivity growth in construction.

C.1 Price Decomposition

Under constant returns and competitive factor markets, zero profit implies that output price equals unit cost. Differentiating this condition gives

$$\Delta \ln P_{i,t} = \bar{s}_{L,i,t}\Delta \ln P^{L}_{i,t} + \bar{s}_{K,i,t}\Delta \ln P^{K}_{i,t} + \bar{s}_{II,i,t}\Delta \ln P^{II}_{i,t} - \Delta \ln A_{i,t}, \tag{C.1}$$

where P^L, P^K, and P^{II} are the implicit price indexes of labor, capital services, and intermediate inputs. The weights are Törnqvist averages,

$$\bar{s}_{j,i,t} = \frac{1}{2}(s_{j,i,t} + s_{j,i,t-1}).$$

Productivity enters with a negative sign because higher TFP lowers unit cost.

Expressing prices relative to the aggregate gross-output price P_{agg} yields

$$\begin{aligned}\Delta \ln \left(\frac{P_{i,t}}{P_{agg,t}}\right) = \bar{s}_{L,i,t}\left(\Delta \ln P^{L}_{i,t} - \Delta \ln P_{agg,t}\right) + \bar{s}_{K,i,t}\left(\Delta \ln P^{K}_{i,t} - \Delta \ln P_{agg,t}\right) \\ + \bar{s}_{II,i,t}\left(\Delta \ln P^{II}_{i,t} - \Delta \ln P_{agg,t}\right) - \Delta \ln A_{i,t}.\end{aligned} \tag{C.2}$$

The first three terms measure cost pressure, while $-\Delta \ln A_{i,t}$ captures the price effect of productivity growth.

C.2 Value-Added Growth Decomposition

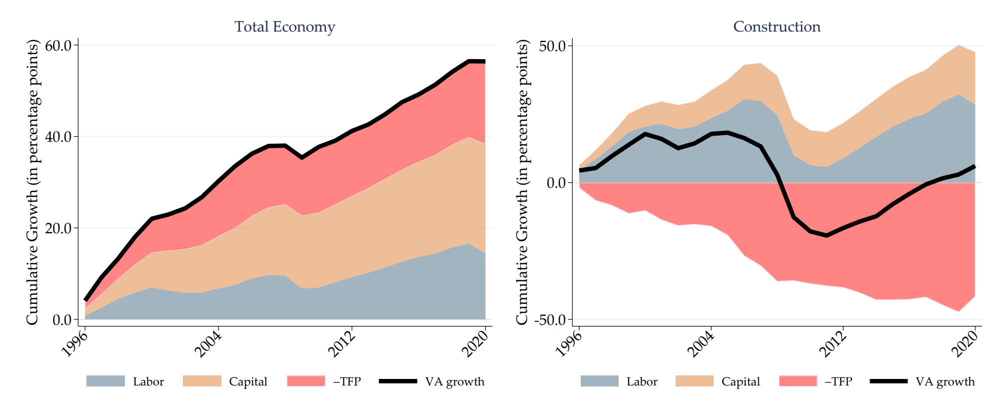
We also decompose real value-added growth into factor contributions. Under constant returns and marginal-product factor pricing,

$$\Delta \ln VA_{i,t} = \bar{s}_{L,i,t}\Delta \ln L_{i,t} + \bar{s}_{K,i,t}\Delta \ln K_{i,t} + \Delta \ln A_{i,t}, \tag{C.3}$$

where L and K are composition-adjusted labor and capital-service indexes, and $\Delta \ln A_{i,t}$ is the Solow residual. EU KLEMS reports these terms as pre-computed contributions, so the identity holds by construction.

Figure C.1 shows that aggregate value-added growth is supported by both factor accumulation and productivity. In construction, by contrast, productivity contributes negatively for much of the sample, suggesting that the sectoral slowdown reflects weak efficiency growth rather than only weak factor accumulation.

Figure C.1: **Cumulative Value-Added Growth Decomposition in the United States**

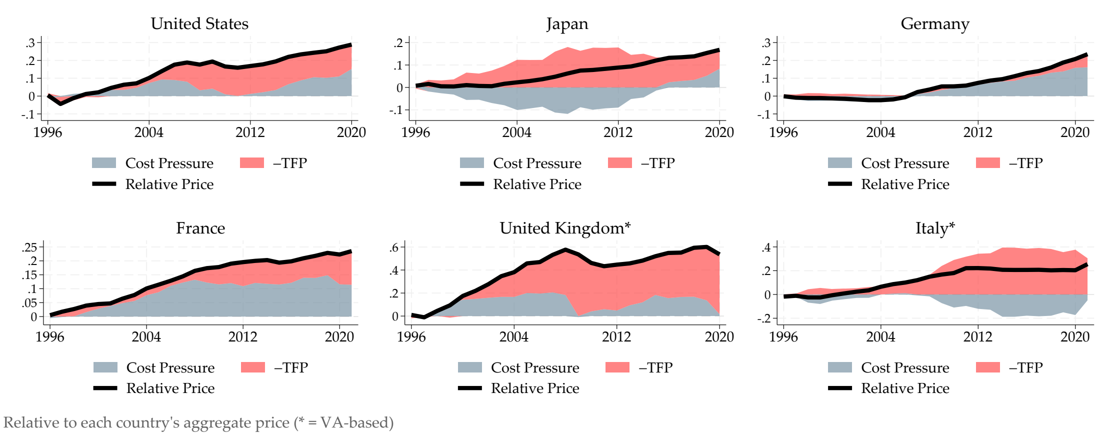


Notes. The figure decomposes cumulative value-added growth into labor, capital, and productivity components. The left panel reports the total economy, and the right panel reports construction. The black line is cumulative value-added growth. The shaded areas show cumulative factor and productivity contributions. In construction, productivity is negative over much of the sample and offsets gains from labor and capital. *Sources.* EU KLEMS 2024 and authors' calculations.

C.3 Cross-Country Evidence

Figure C.2 extends the price decomposition to a cross-country comparison of construction-sector relative prices. It shows that construction prices rise relative to aggregate prices in the United States, Japan, Germany, Italy, France, and the United Kingdom. These results indicate that the U.S. pattern is part of a broader cross-country trend.

Figure C.2: **Cross-Country Decomposition: Cost Pressure vs. Productivity**



Notes. The figure decomposes the construction sector's relative output price into cost pressure and −TFP. A positive −TFP contribution indicates upward price pressure from weak productivity growth. Cost pressure aggregates input-cost growth relative to the aggregate price level. The decomposition uses gross output except for the United Kingdom and Italy, where value added is used because gross-output price indexes are unavailable in EU KLEMS 2024. *Sources.* EU KLEMS 2024 and authors' calculations.

D Detailed Derivations of the Balanced Growth Path

This appendix derives the BGP when both equipment and structures are used in R&D. A BGP is a path on which aggregate variables grow at constant rates and asset allocation shares remain constant. First, the two capital stocks satisfy

$$\dot{K}_E = q_E I_E - \delta_E K_E, \qquad \dot{K}_S = q_S I_S - \delta_S K_S,$$

with investment-specific technical change given by $g_{q_E} = \gamma_E$, and $g_{q_S} = \gamma_S$. Dividing by the corresponding stocks gives

$$g_{K_E} = \frac{q_E I_E}{K_E} - \delta_E, \qquad g_{K_S} = \frac{q_S I_S}{K_S} - \delta_S.$$

On a BGP, g_{K_E} and g_{K_S} are constant. Since investment shares are constant, $g_{I_E} = g_{I_S} = g_Y$. Therefore $q_k I_k / K_k$ is constant for $k \in \{E, S\}$, which implies

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

Log differentiation of output gives

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

Since allocation shares are constant on the BGP, $g_{K_E^Y} = g_{K_E}$ and $g_{K_S^Y} = g_{K_S}$. Using the capital growth rates above,

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

Hence

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

R&D technology is

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

Dividing by A gives

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

For g_A to be constant on the BGP, the right-hand side must have zero growth. Thus,

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

Since R&D allocation shares are constant, $g_{K_E^R} = g_{K_E}$ and $g_{K_S^R} = g_{K_S}$. Therefore,

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

Next, let $\boldsymbol{\alpha} = 1-\alpha_E-\alpha_S$ and $\boldsymbol{\eta} = \eta_E+\eta_S$. The final-goods condition can be written as

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

Substituting this into the innovation condition yields

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

Collecting terms gives

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

Therefore,

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

Equivalently,

$$g_A = \frac{(1-\alpha_E-\alpha_S)n + \left[\eta_E(1-\alpha_S) + \eta_S\alpha_E\right]\gamma_E + \left[\eta_S(1-\alpha_E) + \eta_E\alpha_S\right]\gamma_S}{(1-\phi)(1-\alpha_E-\alpha_S) - (\eta_E+\eta_S)}. \tag{D.2}$$

Output growth follows from the final-goods condition,

$$g_Y = \frac{g_A}{1-\alpha_E-\alpha_S} + \frac{\alpha_E\gamma_E + \alpha_S\gamma_S}{1-\alpha_E-\alpha_S} + n. \tag{D.3}$$

A finite BGP requires

$$(1-\phi)(1-\alpha_E-\alpha_S) > \eta_E + \eta_S. \tag{D.4}$$

E Comparison with Standard Growth Models

To highlight the implications of capital heterogeneity, we compare our model with a one-capital benchmark that aggregates equipment and structures into a single stock K.

E.1 BGP Comparison

The one-capital model is obtained by imposing a common ISTC process, $\gamma_S = \gamma_E \equiv \gamma$, aggregating capital shares as $\alpha_{\text{one}} = \alpha_E + \alpha_S$, and collapsing R&D capital intensities to $\eta_{\text{one}} = \eta_E + \eta_S$. The BGP then implies

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

Output growth satisfies

$$g_Y^{\text{one}} = n + \frac{g_A^{\text{one}} + \alpha_{\text{one}}\gamma}{1-\alpha_{\text{one}}}. \tag{E.2}$$

Structural Drag in the One-Capital Model. The two-capital numerator can be rewritten as

$$(1-\alpha_E-\alpha_S)n + (\eta_E+\eta_S)\gamma_E - [\eta_S(1-\alpha_E) + \eta_E\alpha_S]\,(\gamma_E - \gamma_S). \tag{E.3}$$

Thus, when $\gamma_E > \gamma_S$, slow structures ISTC generates a negative drag term with weight

$$\omega_{\text{drag}} \equiv \eta_S(1-\alpha_E) + \eta_E\alpha_S. \tag{E.4}$$

Relative to the one-capital benchmark, the two-capital model lowers long-run innovation because rapid equipment ISTC cannot be fully transmitted to R&D when structures also enter innovation production. The one-capital model therefore creates aggregation bias by assigning equipment-like efficiency growth to the whole capital stock.

E.2 Model Comparison

We compare three specifications. The first is a one-capital model with R&D, where $Y = AK^{\alpha}L^{1-\alpha}$, $\alpha = \alpha_E + \alpha_S = 0.38$, and $\eta = \eta_E + \eta_S = 0.33$. The second is a no-R&D specification with exogenous TFP growth $g_A = n/(1-\phi) = 0.33\%$. The third is our baseline two-capital model. For the one-capital model, we use two ISTC calibrations. One uses the equipment price decline, following Greenwood et al. (1997); Cummins and Violante (2002). The other uses the aggregate investment price trend, following Justiniano et al. (2011).

Table E.I shows that the one-capital model is highly sensitive to the chosen price series. Using equipment ISTC overpredicts growth, while using aggregate investment ISTC underpredicts it. The two-capital model with endogenous R&D delivers $g_{Y/L} = 1.46\%$, close to the observed U.S. rate of 1.69%. This result reflects the joint role of capital heterogeneity and endogenous innovation.

Table E.I: **Growth Rates in One-Capital and Two-Capital Models**

Model Specification	Without R&D	With R&D
One-Capital Model		
Using Equipment ISTC γ_E	2.29%	3.40%
Using Aggregate Investment ISTC γ_I	0.88%	1.20%
Two-Capital Model		
Using Equipment and Structures ISTC γ_E and γ_S	0.83%	**1.46%**
Data		
U.S. GDP per capita growth, 1970–2020	1.69%	

Notes. This table reports steady-state GDP per capita growth across model specifications. The one-capital model uses either $\gamma_E = 0.0290$ or $\gamma_I = 0.0059$. The two-capital model uses $\gamma_E = 0.0290$ and $\gamma_S = -0.0101$. The empirical benchmark is U.S. real GDP per capita growth from PWT.

F Estimation Procedure, Robustness Checks, and Detailed Derivations for the Nested CES Extension

F.1 Details on Estimation Procedure

We estimate the CES production system using annual U.S. data for 1963–2019. The data construction follows Ohanian et al. (2023). Our baseline uses nonfarm business sector (NFBS) data and estimates the CES specification by GMM.

Production structure and normalization. The estimated parameter vector is $\Theta = (\omega, \theta_M, \theta_S, \rho_0, \rho_M, \rho_S)'$. Effective unskilled labor is normalized as $\widetilde{L}_{U,t} = \exp(2)L_{U,t}$, and skilled labor is scaled in the same units, $\widetilde{L}_{S,t} = \exp(2)L_{S,t}$. This fixes the scale of labor units but leaves ρ_2, equivalently σ_S, as a free parameter.

The CES technology is

$$Y_t = \left[\alpha\left(\lambda K_{E,t}^{\rho_1} + (1-\lambda)\widetilde{L}_{S,t}^{\rho_1}\right)^{\eta/\rho_1} + (1-\alpha)\left(\mu K_{S,t}^{\rho_2} + (1-\mu)\widetilde{L}_{U,t}^{\rho_2}\right)^{\eta/\rho_2}\right]^{1/\eta}. \tag{F.1}$$

Let

$$B_{M,t} = \lambda K_{E,t}^{\rho_1} + (1-\lambda)\widetilde{L}_{S,t}^{\rho_1}, \qquad B_{S,t} = \mu K_{S,t}^{\rho_2} + (1-\mu)\widetilde{L}_{U,t}^{\rho_2}, \qquad D_t = \alpha B_{M,t}^{\eta/\rho_1} + (1-\alpha)B_{S,t}^{\eta/\rho_2}.$$

The model-implied output elasticities are

$$s_{K_E,t} = \frac{\alpha\lambda K_{E,t}^{\rho_1} B_{M,t}^{\eta/\rho_1 - 1}}{D_t}, \qquad s_{K_S,t} = \frac{(1-\alpha)\mu K_{S,t}^{\rho_2} B_{S,t}^{\eta/\rho_2 - 1}}{D_t},$$

$$s_{L_S,t} = \frac{\alpha(1-\lambda)\widetilde{L}_{S,t}^{\rho_1} B_{M,t}^{\eta/\rho_1 - 1}}{D_t}, \qquad s_{L_U,t} = \frac{(1-\alpha)(1-\mu)\widetilde{L}_{U,t}^{\rho_2} B_{S,t}^{\eta/\rho_2 - 1}}{D_t}.$$

GMM moment conditions. The first moment imposes no-arbitrage between structures and equipment returns,

$$m_{1,t+1}(\Theta) = \left[\frac{s_{K_S,t+1} Y_{t+1}}{P_{S,t} K_{S,t+1}} + (1-\delta_{S,t+1})\frac{P_{S,t+1}}{P_{S,t}}\right] - \left[\frac{s_{K_E,t+1} Y_{t+1}}{P_{E,t} K_{E,t+1}} + (1-\delta_{E,t+1})\frac{P_{E,t+1}}{P_{E,t}}\right]. \tag{F.2}$$

The second moment matches the labor share. In the net-labor-share baseline,

$$m_{2,t}^{\text{net}}(\Theta) = \frac{(s_{L_S,t} + s_{L_U,t}) Y_t}{Y_t - P_{E,t}\delta_{E,t} K_{E,t} - P_{S,t}\delta_{S,t} K_{S,t}} - LS_t. \tag{F.3}$$

The gross-labor-share version is

$$m_{2,t}^{\text{gross}}(\Theta) = (s_{L_S,t} + s_{L_U,t}) - LS_t. \tag{F.4}$$

The third moment matches the skilled-to-unskilled wage-bill ratio,

$$m_{3,t}(\Theta) = \frac{s_{L_S,t}}{s_{L_U,t}} - \frac{W_{S,t} L_{S,t}}{W_{U,t} L_{U,t}}. \tag{F.5}$$

Instruments and objective function. The instrument vector is $Z_t = \big(K_{E,t}, K_{S,t}, K_{E,t-1}$ $, K_{S,t-1}, P_{E,t-1}, P_{S,t-1}, t\big)'$. following Ohanian et al. (2023). The estimator imposes

$$\mathbb{E}[Z_t \otimes m_t(\Theta)] = 0, \qquad g_T(\Theta) = \frac{1}{T}\sum_{t=1}^{T} Z_t \otimes m_t(\Theta). \tag{F.6}$$

The GMM estimator solves

$$\widehat{\Theta} = \arg\min_{\Theta} g_T(\Theta)' W_T g_T(\Theta). \tag{F.7}$$

We initialize the optimizer with a grid search over admissible CES curvature and share parameters, then re-estimate from the best grid point. We report substitution elasticities, share parameters, and Wald tests for Cobb-Douglas and common-elasticity restrictions.

F.2 Robustness Checks on Structural Drag

We estimate four specifications by crossing gross and net labor-share measures with stock-based and investment-based structures-price measures. The baseline is the gross labor-share specification with the investment-based structures price.

Table F.I: **CES estimates across specifications**

Panel A. Elasticity of substitution estimates

	Baseline (Gross, Inv.)	Gross, Stock	Net, Stock	Net, Inv.
Substitution elasticities $\hat{\sigma} = 1/(1-\hat{\rho})$				
σ_0 (outer)	1.418	1.422	1.460	1.443
σ_M (equip–skilled)	0.716	0.698	0.725	0.708
σ_S (struct–unskilled)	2.239	1.819	2.125	1.742
CES exponents $\hat{\rho}$ (SE)				
ρ_0	0.295	0.297	0.315	0.307
	(0.013)	(0.019)	(0.016)	(0.011)
ρ_M	−0.396	−0.432	−0.379	−0.413
	(0.030)	(0.044)	(0.021)	(0.024)
ρ_S	0.553	0.450	0.530	0.426
	(0.060)	(0.090)	(0.049)	(0.072)

Panel B. Distribution parameters

	Baseline (Gross, Inv.)	Gross, Stock	Net, Stock	Net, Inv.
ω	0.570	0.569	0.574	0.580
	(0.005)	(0.006)	(0.008)	(0.006)
θ_M	0.245	0.218	0.251	0.229
	(0.019)	(0.025)	(0.013)	(0.014)
θ_S	0.579	0.513	0.559	0.485
	(0.037)	(0.057)	(0.030)	(0.046)

Notes. GMM estimation on NFBS data. Stock uses the stock-based structures price, while Inv. uses the investment-based structures price. Gross and Net refer to labor-share definitions. Standard errors are in parentheses. The baseline result is shown in the first column.

Table F.I shows stable qualitative patterns across specifications. The outer elasticity exceeds one, the equipment–skilled elasticity is below one, and the structures–unskilled elasticity is above one. Thus, the estimates imply top-nest substitution, equipment–skilled complementarity, and structures–unskilled substitutability.

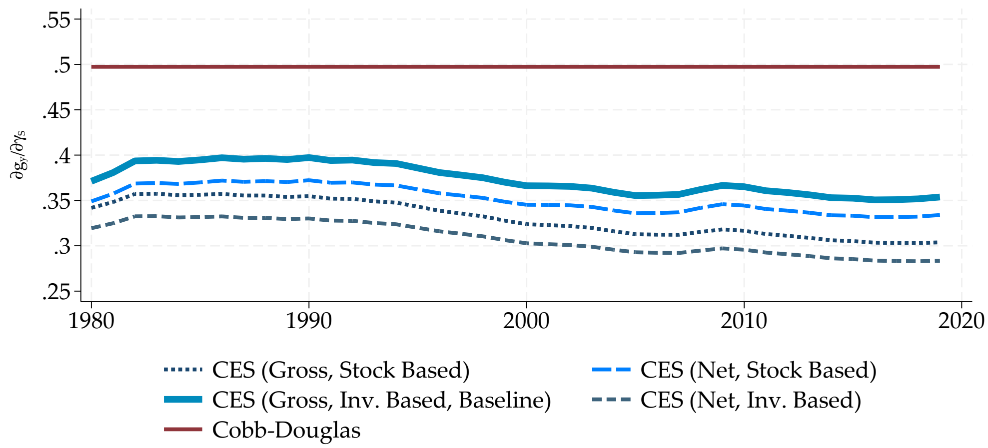
Table F.II confirms that the substitution patterns are statistically distinct. The Cobb-Douglas restrictions are rejected in each nest, and the equality of the two inner elasticities is also rejected. We then compute structural drag under the same four specifications.

Table F.II: **Specification tests**

	Baseline (Gross, Inv.)	Gross, Stock	Net, Stock	Net, Inv.
Wald $\chi^2(1)$ statistics				
$\sigma_0 = 1$	528.0	242.3	390.3	755.0
$\sigma_M = 1$	177.6	98.6	324.0	305.9
$\sigma_S = 1$	86.2	25.3	115.5	34.8
$\sigma_M = \sigma_S$	498.1	202.9	283.7	199.8

Notes. Reported entries are Wald $\chi^2(1)$ statistics. All tests reject at the 1% level. The baseline result is shown in the first column.

Figure F.1: **Structural Drag under Cobb-Douglas and CES**



Notes. The figure compares structural drag under Cobb-Douglas and CES technologies. The red line is the Cobb-Douglas baseline. The blue lines are CES results under Gross/Inv., Gross/Stock, Net/Stock, and Net/Inv. specifications.

Figure F.1 shows that structural drag is smaller under CES than under Cobb-Douglas across all specifications and declines over time.

F.3 Derivation of Structural Drag under Nested CES

The final-goods technology is

$$Y_t = A_t \left[\omega M_t^{\rho_0} + (1-\omega) S_t^{\rho_0}\right]^{1/\rho_0},$$
$$M_t = \left[\theta_M (K_{E,t}^Y)^{\rho_M} + (1-\theta_M)(L_{s,t}^Y)^{\rho_M}\right]^{1/\rho_M},$$
$$S_t = \left[\theta_S (K_{S,t}^Y)^{\rho_S} + (1-\theta_S)(L_{u,t}^Y)^{\rho_S}\right]^{1/\rho_S},$$

where $\rho_j = (\sigma_j - 1)/\sigma_j$ for $j \in \{0, M, S\}$.

Final-goods allocations satisfy

$$L^Y_{s,t} = (1-\ell_t)L_{s,t}, \qquad K^Y_{E,t} = (1-\chi_{E,t})K_{E,t}, \qquad K^Y_{S,t} = (1-\chi_{S,t})K_{S,t}.$$

Log differentiation of each CES nest gives share-weighted growth. With locally fixed allocation terms absorbed into the estimated CES coefficients, the relevant share functions are

$$s_{K_E|M,t} = \frac{\theta_M K_{E,t}^{\rho_M}}{\theta_M K_{E,t}^{\rho_M} + (1-\theta_M)L_{s,t}^{\rho_M}}, \qquad s_{K_S|S,t} = \frac{\theta_S K_{S,t}^{\rho_S}}{\theta_S K_{S,t}^{\rho_S} + (1-\theta_S)L_{u,t}^{\rho_S}},$$

$$s_{M,t} = \frac{\omega M_t^{\rho_0}}{\omega M_t^{\rho_0} + (1-\omega)S_t^{\rho_0}}.$$

Therefore,

$$g_{Y,t} = g_{A,t} + s_{M,t}g_{M,t} + (1-s_{M,t})g_{S,t},$$

where $g_{M,t} = s_{K_E|M,t}g_{K_E^Y,t} + (1-s_{K_E|M,t})g_{L_s^Y,t}, \qquad g_{S,t} = s_{K_S|S,t}g_{K_S^Y,t} + (1-s_{K_S|S,t})g_{L_u,t}$.

Define $\mathbf{a}_{E,t} = s_{M,t}s_{K_E|M,t}$, $\mathbf{a}_{L_s,t} = s_{M,t}(1-s_{K_E|M,t})$, $\mathbf{a}_{S,t} = (1-s_{M,t})s_{K_S|S,t}$, $\mathbf{a}_{L_u,t} = (1-s_{M,t})(1-s_{K_S|S,t})$. Using

$$g_{K_E^Y,t} = g_{K_E,t} - \frac{\dot{\chi}_{E,t}}{1-\chi_{E,t}}, \qquad g_{K_S^Y,t} = g_{K_S,t} - \frac{\dot{\chi}_{S,t}}{1-\chi_{S,t}}, \qquad g_{L_s^Y,t} = g_{L_s,t} - \frac{\dot{\ell}_t}{1-\ell_t},$$

the exact production-side growth equation is

$$g_{Y,t} = g_{A,t} + \mathbf{a}_{E,t}\left(g_{K_E,t} - \frac{\dot{\chi}_{E,t}}{1-\chi_{E,t}}\right) + \mathbf{a}_{S,t}\left(g_{K_S,t} - \frac{\dot{\chi}_{S,t}}{1-\chi_{S,t}}\right) + \mathbf{a}_{L_s,t}\left(g_{L_s,t} - \frac{\dot{\ell}_t}{1-\ell_t}\right) + \mathbf{a}_{L_u,t}g_{L_u,t}.$$

Since R&D technology is $\dot{A}_t = \kappa A_t^{\phi}(K^R_{E,t})^{\eta_E}(K^R_{S,t})^{\eta_S}(L^R_{s,t})^{1-\eta_E-\eta_S}$. and $K^R_{E,t} = \chi_{E,t}K_{E,t}$, $K^R_{S,t} = \chi_{S,t}K_{S,t}$, and $L^R_{s,t} = \ell_t L_{s,t}$,

$$\frac{\dot{g}_{A,t}}{g_{A,t}} = (\phi-1)g_{A,t} + \eta_E\left(g_{K_E,t} + \frac{\dot{\chi}_{E,t}}{\chi_{E,t}}\right) + \eta_S\left(g_{K_S,t} + \frac{\dot{\chi}_{S,t}}{\chi_{S,t}}\right) + (1-\eta_E-\eta_S)\left(g_{L_s,t} + \frac{\dot{\ell}_t}{\ell_t}\right).$$

Let $q_{E,t} = P^{-1}_{E,t}$, $q_{S,t} = P^{-1}_{S,t}$, $\gamma_E = g_{q_E,t}$, and $\gamma_S = g_{q_S,t}$. With $\zeta_{E,t} = K_{E,t}/(q_{E,t}Y_t)$ and $\zeta_{S,t} = K_{S,t}/(q_{S,t}Y_t)$,

$$g_{K_E,t} = g_{Y,t} + \gamma_E + \frac{\dot{\zeta}_{E,t}}{\zeta_{E,t}}, \qquad g_{K_S,t} = g_{Y,t} + \gamma_S + \frac{\dot{\zeta}_{S,t}}{\zeta_{S,t}}.$$

Impose the local closure $\dot{\zeta}_{E,t} = \dot{\zeta}_{S,t} = \dot{\ell}_t = \dot{\chi}_{E,t} = \dot{\chi}_{S,t} = \dot{g}_{A,t} = 0$ and $g_{L_s,t} = g_{L_u,t} = n$ to derive closed-form solution. Then the production block becomes

$$g_{Y,t} = g_{A,t} + (\mathbf{a}_{E,t} + \mathbf{a}_{S,t})g_{Y,t} + \mathbf{a}_{E,t}\gamma_E + \mathbf{a}_{S,t}\gamma_S + (1 - \mathbf{a}_{E,t} - \mathbf{a}_{S,t})n.$$

The knowledge block becomes

$$(1-\phi)g_{A,t} = (\eta_E + \eta_S)g_{Y,t} + \eta_E\gamma_E + \eta_S\gamma_S + (1 - \eta_E - \eta_S)n.$$

Eliminating $g_{A,t}$ gives

$$\Delta_t g_{Y,t} = (\Delta_t + 1)n + \big((1-\phi)\mathbf{a}_{E,t} + \eta_E\big)\gamma_E + \big((1-\phi)\mathbf{a}_{S,t} + \eta_S\big)\gamma_S,$$

where $\Delta_t = (1-\phi)(1 - \mathbf{a}_{E,t} - \mathbf{a}_{S,t}) - (\eta_E + \eta_S)$. Since $g_{y,t} = g_{Y,t} - n$,

$$g_{y,t} = \frac{n + \big((1-\phi)\mathbf{a}_{E,t} + \eta_E\big)\gamma_E + \big((1-\phi)\mathbf{a}_{S,t} + \eta_S\big)\gamma_S}{\Delta_t}.$$

F.4 Derivation of Skill Premium under Nested CES

Let $\pi_t = w_{s,t}/w_{u,t}$. Under cost minimization,

$$\pi_t = \frac{\mathbf{a}_{L_s,t}}{\mathbf{a}_{L_u,t}}\frac{L_{u,t}}{L^Y_{s,t}} = \frac{s_{M,t}(1 - s_{K_E|M,t})}{(1 - s_{M,t})(1 - s_{K_S|S,t})}\frac{L_{u,t}}{L^Y_{s,t}}.$$

With locally constant ℓ_t, log differentiation gives

$$g_{\pi,t} = \frac{d}{dt}\ln\left(\frac{s_{M,t}}{1 - s_{M,t}}\right) + \frac{d}{dt}\ln(1 - s_{K_E|M,t}) - \frac{d}{dt}\ln(1 - s_{K_S|S,t}) + g_{L_u,t} - g_{L_s,t}.$$

The required derivatives are

$$\frac{d}{dt}\ln\left(\frac{s_{M,t}}{1 - s_{M,t}}\right) = \rho_0(g_{M,t} - g_{S,t}),$$

$$\frac{d}{dt}\ln(1 - s_{K_E|M,t}) = -\rho_M s_{K_E|M,t}(g_{K_E,t} - g_{L_s,t}), \quad \frac{d}{dt}\ln(1 - s_{K_S|S,t}) = -\rho_S s_{K_S|S,t}(g_{K_S,t} - g_{L_u,t}).$$

Using $g_{M,t} = g_{L_s,t} + s_{K_E|M,t}(g_{K_E,t} - g_{L_s,t})$, $\quad g_{S,t} = g_{L_u,t} + s_{K_S|S,t}(g_{K_S,t} - g_{L_u,t})$, we obtain

$$g_{\pi,t} = (\rho_0 - 1)(g_{L_s,t} - g_{L_u,t}) + (\rho_0 - \rho_M)s_{K_E|M,t}(g_{K_E,t} - g_{L_s,t}) + (\rho_S - \rho_0)s_{K_S|S,t}(g_{K_S,t} - g_{L_u,t}).$$

Since $\rho_j = 1 - 1/\sigma_j$,

$$g_{\pi,t} = \frac{1}{\sigma_0}(g_{L_u,t} - g_{L_s,t}) + \left(\frac{1}{\sigma_M} - \frac{1}{\sigma_0}\right) s_{K_E|M,t}(g_{K_E,t} - g_{L_s,t}) - \left(\frac{1}{\sigma_S} - \frac{1}{\sigma_0}\right) s_{K_S|S,t}(g_{K_S,t} - g_{L_u,t}).$$