# The Return on Capital in Disaggregated Economies: Theory and Measurement*

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This paper develops a general equilibrium model of firm and investment dynamics to study the sources of the divergence between a persistently high measured return on capital and a declining risk-free rate in the U.S. since the 1980s. The framework delivers a closed-form decomposition of the gap between the two rates into profits, risk premia, capital gains, taxes, capital wedges, and aggregation, together with an identification strategy applicable to standard data sources. Applying the framework to U.S. firms, we find that capital wedges account for about 70 percent of this divergence, while risk premia and profits explain the rest. The rise in wedges is a within-firm phenomenon, associated with intangible capital and hurdle-rate wedges that slow capital accumulation. These same forces imply that the true return on capital has declined alongside the risk-free rate and are also consistent with slower productivity growth and rising stock market valuations.

**Keywords:** Return on capital, cost of capital, investment, intangible capital, discount rates.

**JEL Codes:** D24, D25, E22, E23, E43, G12, G31

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# 1 Introduction

Since the 1980s, the return on safe assets in the U.S. has declined substantially, while the return on capital has remained persistently high. This divergence lies at the center of many debates in macroeconomics and finance. A low safe rate is often interpreted as evidence of a shortage of investment opportunities and secular stagnation (e.g., Summers, 2014). However, persistently high returns on capital challenge this view (e.g., Gomme et al., 2011) and suggest that a growing share of national income accrues to capital owners, potentially fueling wealth inequality (e.g., Piketty, 2014). The distinction also has implications for monetary policy, as it forces central banks to decide which rate should anchor policy decisions (e.g., Reis, 2022).

The existing literature highlights several explanations for this divergence. Caballero et al. (2017) focus on risk premia, while Eggertsson et al. (2021) emphasize the role of profits. Analyzing both jointly, Farhi and Gourio (2018) show that each contributes to the divergence. More recently, Reis (2022) highlights the role of capital frictions. Although all these mechanisms generate a gap between measured returns on capital and the risk-free rate, they imply sharply different conclusions for policy and welfare. Therefore, normative conclusions depend critically on correctly identifying the contribution of each channel in the data. However, no existing study analyzes them jointly within a unified framework, potentially distorting inference about the forces driving the divergence. The objective of this paper is to fill this gap.

To do so, we develop a dynamic general equilibrium theory of the aggregate return on capital in disaggregated economies. The model extends a standard framework of firm and investment dynamics to incorporate capital gains, corporate taxes, profits, risk premia, and capital frictions, delivering three main insights. First, it yields a *closed-form decomposition* of the gap between the measured return on capital and the risk-free rate into the contribution of each force and the role of firm heterogeneity. Second, it provides a framework to *jointly identify* these components using standard data sources by integrating empirical approaches from the literature on asset pricing, industrial organization, and misallocation. Third, it allows us to distinguish between the measured and the *true* return on capital, which in equilibrium equals the risk-free rate plus a risk premium.

Implementing the framework on U.S. firm-level data, we find that capital frictions account for 70 precent of the divergence between the measured return on capital and the risk-free rate. We further show that the increase in capital frictions reflects a slowdown in capital accumulation during periods of rapid sales growth. We identify two candidate explanations for this phenomenon: the growing importance of intangible capital, which adjusts more slowly than tangible capital (e.g., Haskel and Westlake, 2017), and changes in managerial investment practices that have increased firms' required returns on investment (e.g., Gormsen and Huber, 2023). Quantitatively, each accounts for approximately 40 percent of the observed rise in capital wedges. Although the measured return on capital has remained persistently high due to these frictions, the modest role of risk premia implied by our estimates implies a *decline* in the true return on capital in line with the risk-free rate.

In practice, our model features long-lived firms investing in capital under uncertainty about future returns, leading to risk premia. Firms charge markups over marginal cost, generating pure profits, are subject to corporate taxation, and face capital frictions in the form of reduced-form wedges. In this environment, the optimal dynamic investment decision equates the after-tax revenue-based marginal product of capital, adjusted for markups, to a generalized user cost of capital. The latter equals the standard risk-free rate plus depreciation, augmented by capital gains, corporate taxes, risk premia, and capital wedges. In this sense, the framework nests and extends both Hall and Jorgenson (1967) and Hsieh and Klenow (2009). A central implication is that cross-firm variation in the user cost of capital is insufficient to separately identify the role of risk premia and capital frictions.

Aggregating firm-level investment decisions, we derive a closed-form decomposition of the measured return on capital—defined as the ratio of net operating surplus to the value of capital in the economy (e.g., Gomme et al., 2011)—in excess of the risk-free rate into the capital-weighted contributions of capital gains, corporate taxes, risk premia, capital wedges, and pure profits. The decomposition allows us to perform general equilibrium counterfactual analyses that shed light on the relative importance of each factor in driving the divergence between the two returns. It also clarifies the distinction between the measured and the true return on capital, which in equilibrium, due to the implied no-arbitrage condition between risky capital investment and risk-free assets, equals the risk-free rate plus an aggregate risk premium.

Finally, the model delivers an identification strategy for the joint role of each factor in driving firms' differences in the user cost of capital. Capital gains, corporate taxes, and markups follow directly from their definitions and the first-order condition for the variable input. To separately identify the remaining role of risk and frictions, we exploit the asset-pricing definition of risk premia as the covariance between firm returns on capital and the stochastic discount factor, thereby imposing the additional restrictions needed for identification. In practice, the covariance structure implied by risk premia leads naturally to a state-of-the-art empirical asset-pricing two-pass regression approach dating back to

Fama and MacBeth (1973), which we use to recover firm-level risk premia and interpret the remaining unexplained variation in user cost as capital wedges. Therefore, the model provides a unified equilibrium approach to measuring the joint role of profits, taxes, risk premia, and capital frictions in shaping the evolution of the aggregate return on capital.

We demonstrate the empirical relevance and broad applicability of the framework by applying it to conventional U.S. firm-level data. Our analysis draws on Compustat, which provides the balance-sheet information on sales, input costs, and capital needed to implement our measurements and covers the largest firms, accounting for the majority of aggregate capital (e.g., Crouzet and Mehrotra, 2020). We find that Compustat closely mirrors the aggregate measured return on capital reported in the national accounts, making it a suitable laboratory for studying its dynamics.

We measure capital gains using the investment deflator proposed by Gourio et al. (2022) and corporate taxes using statutory tax rates together with depreciation deductions from the data and investment deductions from Atkeson et al. (2024). We measure markups using the static first-order condition for the variable input, following De Loecker and Warzynski (2012), and estimate the required output elasticity of the variable input following Ackerberg and De Loecker (2024, 2026), who show how to recover this elasticity when only revenue data are available.

Using these measurements together with our closed-form decomposition of the gap between the measured return on capital and the risk-free rate, we find that capital wedges account for approximately 70 percent of the documented divergence, having risen substantially over time. Risk premia and profits also contribute positively to the divergence, accounting for roughly 20 and 10 percent, respectively. By contrast, the contributions of corporate taxes and capital gains are quantitatively negligible.

Focusing on the rise in aggregate capital-weighted capital wedges, we find that it is not driven by measurement error nor reallocation across sectors, but instead reflects a broad-based phenomenon affecting the entire distribution of firms. To shed light on the micro-level drivers of this increase, we construct capital wedge quasi-shocks following Hamilton (2018), defined as episodes in which firms experience unusually large changes to their capital wedge. Using local projections as in Jordà (2005), we study the joint dynamics of sales, capital accumulation, and revenue-based marginal products of capital around these episodes. We find that quasi-shock events are characterized by large sales expansions accompanied by relatively modest capital growth, leading to persistent increases in revenue-based returns on capital. Over time, while the magnitude of sales expansions has remained broadly stable, capital accumulation around these episodes has slowed substantially, generating increasingly persistent rises in revenue-based marginal products of capital.

We identify two candidate explanations for the documented decline in the speed of capital accumulation during episodes of firm expansion: the rising importance of intangible capital and changes in managerial investment behavior. First, intangible capital accumulates substantially more slowly than tangible capital, consistent with recent evidence on higher financial frictions (e.g., Falato et al., 2022) and adjustment costs (e.g., Chiavari and Goraya, 2025). As a result, its growing importance explains roughly 40 percent of the slowdown in aggregate capital accumulation—and the corresponding rise in the revenue-based marginal product of capital—during these expansion episodes. Second, hurdle-rate wedges—defined as managers requiring persistently higher returns on investment than their perceived cost of capital (e.g., Gormsen and Huber, 2023)—are closely associated with our measure of capital wedges and also help explain why firms invest less during periods of rapid sales growth. We find that the rise in hurdle-rate wedges help explain an additional 40 percent of the observed slowdown.

Our findings have several macroeconomic implications beyond the divergence between the measured return on capital and the risk-free rate. Our finding that the aggregate risk premium has increased only modestly over time implies that the true return on capital has also declined since the 1980s, in contrast to the stable behavior of the measured return on capital, broadly tracking the decline in the risk-free rate.

We further find that rising dispersion in capital wedges and markups jointly generate a substantial drag on productivity in our framework, potentially contributing to the weak growth performance of the U.S. economy since the 1980s (e.g., Gordon, 2012). We also find that a large share of the rise in stock market valuations is driven by rising free cash flows, consistent with Atkeson et al. (2025). Much of this increase reflects growing frictions that raise the revenue-based marginal product of capital, partly associated with the rising importance of intangible capital, in line with Crouzet and Eberly (2023) and Ilut et al. (2024), while pure profits play a more modest role. Finally, because of its accounting nature, the model is also consistent with a broader set of secular trends, including rising concentration, increasing intangible investment rates, declining tangible capital accumulation, and changing public-firm dynamism.

**Related literature.** This paper relates to several strands of literature. We contribute to the literature on the divergence between the return on capital and the risk-free rate by developing a framework that delivers a novel closed-form decomposition and identification of the main firm-level forces behind this phenomenon. Most existing studies focus on one or a small subset of channels, with their conclusions constrained by the limited ability of aggregate data to distinguish between them. For example, Eggertsson et al. (2021) emphasize rising profits, Caballero et al. (2017) and Marx et al. (2021) focus on risk premia, Farhi and Gourio (2018) stress the joint role of the two, and Reis (2022) highlight capital frictions. In contrast, we analyze all these explanations jointly.[1]

Our findings identify capital wedges as the primary force driving this divergence. We trace their rise to a slowdown in firm-level capital accumulation associated with the growing importance of intangible capital and changes in managerial investment behavior. In doing so, the paper connects to a large literature documenting the role of financial frictions and adjustment costs in the accumulation of intangible capital (e.g., Ai et al., 2020; Belo et al., 2022; Bhandari et al., 2025; Caggese and Pérez-Orive, 2022; Chiavari and Goraya, 2025; Crouzet and Eberly, 2023; Falato et al., 2022; Peters and Taylor, 2017; Zhang, 2024) and to recent work documenting rising hurdle-rate wedges in corporate investment decisions (e.g., Gormsen and Huber, 2023).

Moreover, because the forces driving the return on capital also shape firms' valuations, our paper is closely related to the literature on the rise in stock market valuations. Existing explanations emphasize the role of risk premia, profits, and corporate taxation (e.g., Corhay et al., 2020; Greenwald et al., 2025; McGrattan, 2023). While each of these forces contributes to the rise in valuations, our results suggest that much of the increase is consistent with rising free cash flows, as in Atkeson et al. (2025), largely driven by growing capital frictions. By increasing the gap between the revenues generated by capital and the effective cost of generating them, these frictions raise firms' cash flows and valuations. In this respect, our findings are closely related to Crouzet and Eberly (2023) and Ilut et al. (2024), who also emphasize the role of frictions associated with intangible capital in explaining the evolution of equity valuations.

Methodologically, the paper connects three strands of the literature: misallocation, empirical asset pricing, and the user cost of capital. The seminal work in the reduced-form misallocation literature is Hsieh and Klenow (2009), who uses firm-level wedges to quantify the aggregate consequences of distortions, while subsequent contributions extend this framework along several dimensions (e.g., Baqaee and Farhi, 2020; Bils et al., 2021; David and Venkateswaran, 2019; Faria-e Castro et al., 2025).[2] Our contribution is to introduce an asset-pricing restriction by modeling intertemporal investment under un-

[1] Rachel (2025) similarly emphasizes the importance of studying different explanations within a unified framework, but does so in the context of the risk-free natural rate.

[2] Recently, production-function-free approaches have used (quasi-)experimental variation to estimate marginal products directly (e.g., Carrillo et al., 2023; Hughes and Majerovitz, 2023). While powerful, such approaches typically require specialized sources of variation that are not available in conventional firm-level datasets.

certainty, allowing to disentangle capital wedges from risk premia, which is crucial to separately identify all the forces shaping the aggregate return on capital. In this respect, our paper is closest to David et al. (2022), who introduce risk premia parametrically into a misallocation framework. In contrast, our approach is non-parametric, accommodates markups, taxes, capital gains, and broad capital frictions beyond adjustment costs, and can be implemented using standard firm-level data.

In doing so, the paper also relates to the empirical literature on asset pricing and the user cost of capital, dating back to Fama and MacBeth (1973) and Hall and Jorgenson (1967), respectively. Our framework delivers a generalized dynamic user cost of capital that includes risk premia and capital wedges, and shows how asset-pricing restrictions can be used within a production-based framework to separately identify the two.

**Outline.** Section 2 reviews the facts on the divergence between the return on capital and the risk-free rate. Section 3 introduces our framework. Section 4 describes the data and the measurement. Section 5 presents the main results, and Section 6 discusses macro implications. Section 7 concludes.

# 2 The Return on Capital and the Risk-Free Rate: Measurement and Evidence

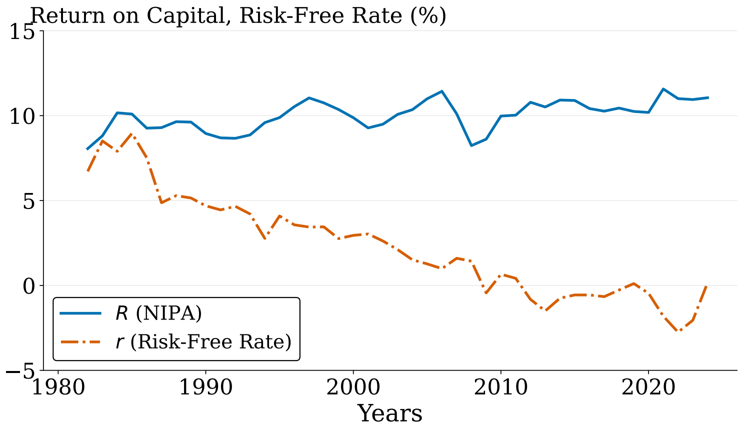
This section summarizes the empirical facts on the evolution of the return on capital and the risk-free rate and clarifies how the former is measured in the literature.

The risk-free rate is typically proxied by observed yields on safe assets (e.g., Rachel and Summers, 2019). In contrast, the aggregate return on capital is not directly observable and is instead constructed from national accounts. The standard measure, widely used in the literature (e.g., Gomme et al., 2011; Reis, 2022) and dating back at least to Nordhaus et al. (1974) and Feldstein et al. (1977), defines the measured return on capital $R$ as the share of net output accruing to capital relative to the market value of the capital stock:

$$R \equiv \frac{Y - \delta QK - WL}{QK}, \tag{1}$$

where $Y$ denotes output, $WL$ the labor bill with wage $W$ and labor input $L$, $K$ the physical capital stock, $Q$ the price of installed capital, and $\delta$ the depreciation rate. The numerator therefore measures income accruing to capital as output net of depreciation and labor compensation, while the denominator scales this flow by the value of the capital stock.

**Figure 1:** Measured Return on Capital and Risk-Free Rate




*Note.* The figure plots the measured return on capital and the risk-free rate, in percent, since 1982. The return on capital is constructed using Equation (1) with NIPA data, as explained in the main text. The risk-free rate is the yield on U.S. Treasury securities with a 10-year constant maturity, adjusted using expected inflation from the Michigan Survey.

In the data, we proxy the risk-free rate using the real market yield on U.S. Treasury securities with a 10-year constant maturity. We construct the measured return on capital for the business sector as net operating surplus net of two-thirds of mixed income, divided by the value of the total capital stock.[3] Appendix B.2 provides details on the construction of the risk-free rate and the measured return on capital. Alternative measures of safe returns display similar trends,[4] while variations in the construction of the measured return on capital—such as accounting for public capital, real estate, or focusing on the whole economy instead of the business sector—do not materially affect its measurement (e.g., Gomme et al., 2011; Reis, 2022).

Figure 1 shows that since the 1980s the risk-free rate has declined substantially, while the measured return on capital has remained broadly stable. This divergence is a well-established feature of the data and is particularly notable as it follows decades of convergence between the two rates (see Figure B.1 in Appendix B.2 for the longer historical evolution of these measures back to 1960).

From the perspective of Equation (1), this divergence can arise from two distinct sources. First, the measured return may differ from the true return on capital because it relies on assumptions unlikely to be true in the data—namely, the absence of pure profits, taxes, capital gains on the existing capital stock, and distortions or frictions affecting

[3] National accounts attribute all mixed income to capital, although it likely includes a labor component. Following the literature (e.g., Caselli and Feyrer, 2007; Gutiérrez and Piton, 2020), we attribute two-thirds of mixed income to labor, adjusting both the labor share and the measure of capital income accordingly.

[4] Rachel and Summers (2019) documents the pervasive decline in safe returns across a range of assets and measures, including corporate bond yields, equity-based measures, and estimates of $r^{\star}$ from central banks.

investment decisions. Second, even when the measured return coincides with the true return, the latter need not equal the risk-free rate, but instead equals the risk-free rate plus a risk premium reflecting compensation for aggregate risk.

The observed divergence can therefore reflect the presence of factors ruled out by the assumptions underlying the standard measure, risk premia, or both. The next section develops a framework that allows these forces to be jointly identified from their firm-level origins and mapped into the aggregate divergence of interest.

# 3 Model

This section develops a parsimonious disaggregated dynamic general equilibrium framework that links capital gains, taxes, risk premia, capital frictions, and profits to firm-level investment decisions and to the aggregate divergence between the measured return on capital and the risk-free rate. The model delivers three main results. First, firm-level investment decisions imply a generalized user cost of capital equal to an adjusted revenue-based marginal product of capital, which provides the basis for jointly identifying the forces shaping firms' investment conditions. Second, the measured firm-level return on capital admits an exact decomposition into the economic forces of interest. Third, these firm-level objects aggregate exactly into the cumulative divergence between the measured aggregate return on capital and the risk-free rate, thereby enabling closed-form counterfactual exercises.

## 3.1 Environment

Time is discrete and indexed by $t \in \{0, 1, \dots\}$. The economy is populated by a continuum of long-lived firms indexed by $j \in \mathcal{J}_t$, discounting future payoffs using an exogenous stochastic discount factor $M_{t+1}$.[5]

**Primitives.** Firm $j$ produces a differentiated good using the technology

$$q_{jt} = z_{jt} \ell_{jt}^{\mathcal{E}_\ell} k_{jt}^{\mathcal{E}_k}, \tag{2}$$

[5]We abstract from microfounding the stochastic discount factor because none of the results below depend on the details of preferences or firm ownership. However, this can be easily achieved via a standard representative-household block in which households are subject to marginal utility shocks. These shocks allow the model to accommodate non-fundamental volatility in asset prices—which has been emphasized since at least Campbell and Shiller (1988)—and to rationalize ex post any observed sequence of $M_{t+1}$ in the data through appropriate realizations.

where $q_{jt}$ is output, $z_{jt}$ is Hicks-neutral productivity, $\ell_{jt}$ is a variable input, $k_{jt}$ is the capital stock, $\mathcal{E}_\ell$ and $\mathcal{E}_k$ are the output elasticities of the variable input and capital, respectively. Firms also incur a fixed overhead cost $\phi_{jt}$ associated with operating the production technology.

Capital accumulates according to

$$k_{jt+1} = (1 - \delta_{jt})k_{jt} + x_{jt}, \tag{3}$$

where $\delta_{jt} \in (0, 1)$ is the firm-specific depreciation rate and $x_{jt}$ denotes gross investment. Capital goods are purchased at price $Q_t$, defined as the price of investment relative to the numeraire.[6] In addition to physical capital, each firm can trade a one-period risk-free bond $b_{jt}$ at price $(1 + r_t)^{-1}$.

**Taxation.** Firms are subject to corporate taxation, following Atkeson et al. (2024). After-tax dividends are

$$\begin{aligned} d_{jt} &= p_{jt}q_{jt} - W_t\ell_{jt} - \phi_{jt} - Q_t x_{jt} \\ &\quad - \tau_t^c \left( p_{jt}q_{jt} - W_t\ell_{jt} - \phi_{jt} - \delta_{k,jt}Q_{t-1}k_{jt} - \delta_{x,jt}Q_t x_{jt} \right) - b_{jt} + \frac{b_{jt+1}}{1 + r_t}, \end{aligned} \tag{4}$$

where $\tau_t^c$ is the corporate tax rate, $\delta_{k,jt}Q_{t-1}k_{jt}$ is deductible depreciation valued at historical cost, and $\delta_{x,jt} \in [0, 1]$ governs investment deductibility, ranging from no deductibility ($\delta_{x,jt} = 0$) to full expensing ($\delta_{x,jt} = 1$).[7]

**Markups.** Following Baqaee and Farhi (2020) we assume that each firm faces downward-sloping demand for its product, and rather than fully specifying the demand side, we summarize it by a firm-level exogenous markup $\mu_{jt}$, interpreted as the ratio of price to marginal cost. This reduced-form treatment is sufficient for our purposes and keeps the analysis focused on capital accumulation and return measurement.

[6] We use a single economy-wide investment price $Q_t$, abstracting from firm-level capital-good heterogeneity. This is standard and is also consistent with the aggregation logic in Gourio et al. (2022).

[7] For simplicity, in Equation (4) we assume that interest expenses are not tax-deductible, which allows us to avoid specifying separate Euler equations for bond holdings of households and firms. This assumption is not consequential for the results that follow, as it does not affect the firm's capital Euler equation, which is the focus of the current paper. In reality, firms are permitted to deduct interest expenditures from their taxable income, which would introduce a wedge between the firm's after-tax cost of debt and the market interest rate, making debt financing subsidized relative to equity (Modigliani and Miller, 1963). This wedge would induce firms to act as net borrowers and households as net lenders in equilibrium. Crucially, however, the risk-free rate would still be ultimately pinned down by the household's stochastic discount factor through market clearing—exactly as in the current formulation.

**Capital wedges.** Investment decisions are likely to be affected by a number of additional factors beyond productivity, installed capital, taxes, and markups, including financial frictions, regulatory distortions, adjustment costs, organizational constraints, or unmodeled heterogeneity in capital technologies. Rather than taking a stand on the precise nature of these forces, we remain agnostic and, following the spirit of Hsieh and Klenow (2009), summarize them in a dynamic setting through a reduced-form constraint on firms' effective capacity to expand capital:

$$\frac{(1-\tau_t^c\delta_{x,jt})Q_t k_{jt+1}}{1+r_t} \leq \kappa_{jt}, \tag{5}$$

where $\kappa_{jt}$ captures the maximum effective scale of capital accumulation that can be implemented at time $t$.[8] We refer to the Lagrange multiplier $\nabla_{jt+1}$ associated with constraint (5) as the capital wedge, capturing the shadow value of relaxing the firm's effective constraint on capital expansion.[9] The $t+1$ subscript reflects that the wedge applies to the choice of next-period capital $k_{jt+1}$ chosen at time $t$, and is therefore known at time $t$. In a slight abuse of terminology, we refer to $\nabla_{jt+1}$ as a "capital wedge" or "friction" throughout the paper. Section 5 shows how some progress can be made in further disentangling its underlying sources.

## 3.2 Firm Problem and Characterization

**Firm problem.** Each firm chooses its variable input $\ell_{jt}$, next-period capital $k_{jt+1}$, and next-period bond holdings $b_{jt+1}$ to maximize the discounted value of after-tax dividends:

$$\max_{\{\ell_{jt},k_{jt+1},b_{jt+1}\}_{t=0}^{\infty}} \mathbb{E}_0 \sum_{t=0}^{\infty}\left(\prod_{s=0}^{t-1} M_{s+1}\right) d_{jt}, \tag{6}$$

subject to (2)-(5).

[8] The constraint is defined in terms of the present-discounted effective after-tax cost of next-period capital. This normalization is adopted purely for notational convenience, as it simplifies the subsequent equilibrium conditions, similarly to David and Venkateswaran (2019), but has no substantive implications for the results.

[9] Treating the wedge $\nabla_{jt+1}$ as a shadow cost is natural in the present environment because all observed production-related expenditures recorded in firms' books are already accounted for through variable input costs, investment expenditures, and overhead costs. Modeling wedges as additional observed expenditures would therefore risk double counting, since many of the underlying costs are already embedded in residual expenditure categories within overhead expenses. Instead, the wedge should be interpreted as an *as-if* cost that distorts firms' investment behavior without necessarily corresponding to separately observed accounting expenditures.

**Optimality conditions.** The static optimality condition for the variable input is:

$$\mu_{jt} = \frac{MRPL_{jt}}{W_t}, \tag{7}$$

where $MRPL_{jt} \equiv \mathcal{E}_\ell \frac{p_{jt} q_{jt}}{\ell_{jt}}$ is the revenue-based marginal product of the variable input. Equation (7) equates the revenue-based marginal product of the variable input over the price of the variable input to the markup, as in Hall (1988) and De Loecker and Warzynski (2012).

The dynamic optimality conditions for the risk-free bond and capital, expressed for notational convenience lagged by one period, are:

$$1 = \mathbb{E}_{t-1}\left[M_t(1 + r_{t-1})\right], \tag{8}$$

$$1 = \mathbb{E}_{t-1}\left[M_t(1 + \mathcal{R}_{jt})\right], \tag{9}$$

where the net return on capital is

$$\mathcal{R}_{jt} \equiv \mathcal{R}^{\nabla}_{jt} - \nabla_{jt}, \tag{10}$$

and the return before capital wedges is

$$\mathcal{R}^{\nabla}_{jt} \equiv \frac{1 - \tau^c_t}{(1 - \tau^c_{t-1}\delta_{x,jt-1})\mu_{jt}} \frac{MRPK_{jt}}{Q_{t-1}} + \frac{(1 - \tau^c_t \delta_{x,jt})(1 - \delta_{jt})Q_t}{(1 - \tau^c_{t-1}\delta_{x,jt-1})Q_{t-1}} + \frac{\tau^c_t \delta_{k,jt}}{1 - \tau^c_{t-1}\delta_{x,jt-1}} - 1, \tag{11}$$

where $MRPK_{jt} \equiv \mathcal{E}_k \frac{p_{jt} q_{jt}}{k_{jt}}$ denotes revenue-based marginal product of capital. The first three terms in (11) correspond, respectively, to the adjusted revenue-based marginal product of capital, capital gains net of depreciation and tax adjustments, and the depreciation tax shield. Equation (10) therefore extends the static framework of Hsieh and Klenow (2009) to a dynamic environment with taxes, capital gains, and risk premia. Equations (8) and (9) imply that, at the margin, firms are indifferent between investing in capital and holding the risk-free bond.

**Optimal capital choice and the user cost.** We can now combine Equation (8)-(11) to characterize the user cost of capital and the optimal capital choice through the following Lemma.

**Lemma 1** *The adjusted revenue-based marginal product of capital,* $\frac{1-\tau^c_t}{(1-\tau^c_{t-1}\delta_{x,jt-1})\mu_{jt}} \frac{MRPK_{jt}}{Q_{t-1}}$*, equals* *the user cost of capital, $uc^k_{jt}$, and satisfies*

$$\frac{1-\tau^c_t}{(1-\tau^c_{t-1}\delta_{x,jt-1})\mu_{jt}}\frac{MRPK_{jt}}{Q_{t-1}} = r_{t-1} + \delta_{jt} + \boldsymbol{\varrho}_{jt} + \boldsymbol{\tau}_{jt} + \boldsymbol{\nabla}_{jt} + \boldsymbol{\zeta}_{jt} \equiv uc^k_{jt}, \quad \forall j \in \mathcal{J}_t, \tag{12}$$

*where each term is defined as follows: (i) $\boldsymbol{\varrho}_{jt} \equiv \frac{(1-\tau^c_t\delta_{x,jt})(1-\delta_{jt})}{1-\tau^c_{t-1}\delta_{x,jt-1}}\left(1-\frac{Q_t}{Q_{t-1}}\right)$ denotes the capital gains; (ii) $\boldsymbol{\tau}_{jt} \equiv \frac{(1-\delta_{jt})(\tau^c_t\delta_{x,jt}-\tau^c_{t-1}\delta_{x,jt-1})-\tau^c_t\delta_{k,jt}}{1-\tau^c_{t-1}\delta_{x,jt-1}}$ denotes the taxes; (iii) $\boldsymbol{\nabla}_{jt} \equiv \nabla_{jt} + \varepsilon_{jt}$ denotes the wedges;[10] and (iv) $\boldsymbol{\zeta}_{jt} = \boldsymbol{\beta}_{jt}\boldsymbol{\lambda}_t$ denotes the risk premium, with $\boldsymbol{\beta}_{jt} \equiv \frac{\mathbb{C}ov_{t-1}[M_t, \mathcal{R}^{\nabla}_{jt}]}{\mathbb{V}ar_{t-1}[M_t]}$ representing firm-level exposure to aggregate risk and $\boldsymbol{\lambda}_t \equiv -\frac{\mathbb{V}ar_{t-1}[M_t]}{\mathbb{E}_{t-1}[M_t]}$ representing the aggregate price of risk.*

**Proof.** See Appendix A.1. ■

Equation (12) extends the classic user-cost formulation of Hall and Jorgenson (1967) to a stochastic, firm-level environment with taxes, markups, risk, and capital wedges. The adjusted revenue-based marginal product of capital is equated to a generalized user cost $uc^k_{jt}$, defined by the risk-free rate and depreciation, and augmented by four components: capital gains $\boldsymbol{\varrho}_{jt}$, taxes $\boldsymbol{\tau}_{jt}$, wedges $\boldsymbol{\nabla}_{jt}$, and risk premia $\boldsymbol{\zeta}_{jt}$. The risk premium takes a standard asset pricing formulation (e.g., Cochrane, 2009) and equals the product of the firm's exposure to aggregate risk, $\boldsymbol{\beta}_{jt}$, and the aggregate price of risk, $\boldsymbol{\lambda}_t$. The augmented wedge $\boldsymbol{\nabla}_{jt}$ combines the original capital wedge $\nabla_{jt}$ with the expectational error $\varepsilon_{jt}$. We group these without loss of generality, as both terms capture residual variation in the revenue-based marginal product of capital without conveying additional separate information, and hereafter, we refer to $\boldsymbol{\nabla}_{jt}$ simply as the capital wedge.

Economically, Equation (12) characterizes the forces shaping firms' optimal capital choices through their effect on the adjusted revenue-based marginal product and the user cost of capital. Holding fixed the revenue-based marginal product of capital, firms invest less when markups are higher, since a larger markup lowers the marginal return generated by an additional unit of capital. Similarly, higher taxes, larger capital wedges, or greater exposure to aggregate risk increase the required return on investment and therefore reduce desired future capital holdings. By contrast, positive capital gains lower the effective cost of holding capital by increasing the future resale value of installed capital, thereby encouraging investment.

Lemma 1 immediately implies a non-identification result.

[10] Where $\varepsilon_{jt}$ represents an expectational error.

**Corollary 1** *The difference between the adjusted revenue-based marginal product of capital and the risk-free rate plus depreciation can identify at most the joint effect of capital wedges $\boldsymbol{\nabla}_{jt}$ and risk premia $\boldsymbol{\zeta}_{jt}$.*

**Proof.** Follows immediately from Lemma 1. ■

Corollary 1 shows that even if capital gains and taxes are perfectly observed, wedges and risk premia cannot be separately identified from this single empirical moment, i.e., the difference between the adjusted revenue-based marginal product of capital and the risk-free rate plus depreciation. More broadly, it underscores that the revenue-based marginal product of capital responds jointly to all four components in Equation (12).

Analyses that omit any one of these components mechanically reassign its variation to the remaining terms. Before discussing how the model can be used to separately identify risk premia and capital wedges, we next turn to its main result: a closed-form characterization of how the firm-level forces discussed thus far jointly determine the aggregate measured return on capital and, in turn, the documented divergence that is the focus of the paper.

## 3.3 General Equilibrium

For every period $t \in [0, \infty)$, given initial conditions $\{k_{j0}, b_{j0}\}_{j \in \mathcal{J}_0}$ and exogenous processes $\{M_t, \mathcal{J}_t, z_{jt}, \phi_{jt}, \delta_{jt}, Q_t, \mu_{jt}, \tau_t^c, \delta_{k,jt}, \delta_{x,jt}, \kappa_{jt}\}_{t=0}^{\infty}$, a *sequential general equilibrium* is a set of prices $\{p_{jt}, W_t, r_t\}$, allocations $\{q_{jt}, \ell_{jt}, k_{jt+1}, b_{jt+1}\}$, and wedges $\{\nabla_{jt+1}\}$ such that: (i) each firm sets its price as the relevant markup over marginal cost and maximizes the expected present discounted value of dividends in (6) subject to the relevant constraints (2)-(5);[11] and (ii) goods, variable input, and bond markets clear.

## 3.4 Micro-to-Macro Link

We now link the firm-level objects derived above to the aggregate divergence between the measured return on capital and the risk-free rate.

**Measured firm-level return.** Building on the commonly used definition of the return on capital in the literature reviewed in Section 2, we define the measured firm-level return on

[11]This definition of general equilibrium mirrors the one in Baqaee and Farhi (2020), extended to our dynamic setting.

capital as the firm's net operating surplus over the value of its installed capital as follows:

$$R_{jt} \equiv \frac{p_{jt}q_{jt} - \phi_{jt} - \delta_{jt}Q_{t-1}k_{jt} - W_t\ell_{jt}}{Q_{t-1}k_{jt}}. \tag{13}$$

The numerator is sales net of variable inputs, overhead costs, and depreciation, and the denominator is the replacement value of the capital stock.

**Proposition 1** *The measured firm-level return on capital can be decomposed as*

$$R_{jt} = r_{t-1} + \boldsymbol{\zeta}_{jt} + \boldsymbol{\varrho}_{jt} + \boldsymbol{\tau}_{jt} + \boldsymbol{\nabla}_{jt} + \boldsymbol{\pi}_{jt}, \tag{14}$$

*where*

$$\boldsymbol{\pi}_{jt} \equiv \frac{p_{jt}q_{jt} - W_t\ell_{jt} - uc^k_{jt}Q_{t-1}k_{jt} - \phi_{jt}}{Q_{t-1}k_{jt}}, \tag{15}$$

$$= \left(1 - \frac{\left(\frac{1-\tau^c_t}{1-\tau^c_{t-1}\delta_{x,jt-1}}\right)\mathcal{E}_k + \mathcal{E}_\ell}{\mu_{jt}}\right)\frac{p_{jt}q_{jt}}{Q_{t-1}k_{jt}} - \frac{\phi_{jt}}{Q_{t-1}k_{jt}}; \tag{16}$$

*which represents pure profits per unit of capital.*

**Proof.** See Appendix A.2. ■

Proposition 1 is the central result of the model. It provides a unified decomposition of the measured return on capital into six distinct components: the risk-free rate, risk premium, capital gains on the existing capital stock, corporate taxes, capital wedges, and pure profits. While the first five objects have already been discussed, it is useful to clarify the interpretation of profits in this context.

The relevant object for the theory is pure profits per unit of capital, $\boldsymbol{\pi}_{jt}$. Conceptually, these correspond to revenues net of the economic cost of all productive inputs and overhead costs. In equilibrium, firms compensate labor through wages and capital according to the generalized user cost characterized in Lemma 1. Economically, pure profits thus reflect rents associated with forces such as market power or non-constant returns to scale that are not exhausted by overhead costs.

This notion is distinct from after-tax free cash flows, which instead correspond to Equation (4) and include not only pure profits, but also the return on installed capital net of investment expenditures, taxes, and financing costs. Put differently, profits measure the surplus generated by production, whereas free cash flows measure the net resources available to distribute to firm owners after investment and financing decisions are taken into account, and are what drives firms' valuations in the model. This distinction will become important later in the paper when comparing the evolution of pure profits and valuations in the data.

Because each component of Proposition 1 is written in terms of measurable objects—whose construction and identification using standard data sources are described in Section 3.5—the decomposition is empirically operational. This allows us to quantify the contribution of each force to the divergence between the measured return on capital and the risk-free rate and to conduct counterfactual exercises that isolate their respective roles.

The proposition also highlights a fundamental identification challenge in the common practice of analyzing candidate explanations in isolation. Because the measured return on capital conflates several distinct economic forces, analyses that omit some components necessarily attribute their variation to those that remain. Our framework addresses this problem by jointly accounting for all components simultaneously, with the standard approach emerging as a limiting special case.

Before turning to aggregation, it is useful to clarify the relationship between the true return on capital and the risk-free rate.

**Corollary 2** *No-arbitrage between risky capital investment and risk-free assets implies that the true return on capital satisfies*

$$\mathbb{E}_{t-1}\mathcal{R}_{jt} = r_{t-1} + \zeta_{jt}. \tag{17}$$

**Proof.** Follows immediately from Equations (8) and (9). ■

The corollary clarifies the relationship between the true return on capital and the risk-free rate. In equilibrium, the two can differ only because investors require compensation for bearing risk. It also helps clarify the distinction between the measured and true returns on capital. The two coincide only in the special case in which capital gains, taxes, capital wedges, and pure profits are jointly zero—precisely the assumptions underlying the conventional measure of the return on capital. When these forces are present, the measured return reflects movements in both the true return on capital and these additional components. For example, an increase in pure profits, which is not part of the true return on capital, is nevertheless attributed to the measured return on capital under the zero-profit assumption implicit in standard measurement.

We now turn to aggregation and show how these firm-level forces jointly determine the dynamics of the aggregate return on capital.

**Measured aggregate return.** To link these measured firm-level returns to the aggregate divergence of interest, we start from the definition of the measured aggregate return on capital $R_t$ presented in Section 2, which can be expressed as:

$$R_t = \frac{Y_t - \delta_t Q_{t-1} K_t - W_t L_t}{Q_{t-1} K_t}, \tag{18}$$

$$= \sum_{j \in \mathcal{J}_t} \omega_{jt} \left( \frac{p_{jt} q_{jt} - \phi_{jt} - \delta_{jt} Q_{t-1} k_{jt} - W_t \ell_{jt}}{Q_{t-1} k_{jt}} \right), \tag{19}$$

$$= \sum_{j \in \mathcal{J}_t} \omega_{jt} R_{jt}, \tag{20}$$

where $Y_t - W_t L_t \equiv \sum_j (p_{jt} q_{jt} - \phi_{jt} - W_t \ell_{jt})$ is the total GDP net of the aggregate wage bill, $\delta_t K_t \equiv \sum_j \delta_{jt} k_{jt}$ is the total aggregate depreciation, $K_t \equiv \sum_j k_{jt}$ is the aggregate capital, and $\omega_{jt} = k_{jt}/K_t$ is the firm-level capital share. Equations (18)-(20) demonstrate that the measured aggregate return on capital can be represented as the capital-weighted average of the measured firm-level returns on capital.

**Lemma 2** *The cumulative difference between the measured aggregate return on capital and the risk-free rate is*

$$\Delta_t (R_t - r_{t-1}) = \Delta_t \boldsymbol{\zeta}_t + \Delta_t \boldsymbol{\varrho}_t + \Delta_t \boldsymbol{\tau}_t + \Delta_t \boldsymbol{\nabla}_t + \Delta_t \boldsymbol{\pi}_t, \tag{21}$$

*where* $\Delta_t x_t \equiv x_t - x_{t_0}$*, with* $t_0$ *denoting the base year,* $\boldsymbol{\zeta}_t \equiv \sum_j \omega_{jt} \boldsymbol{\zeta}_{jt}$, $\boldsymbol{\varrho}_t \equiv \sum_j \omega_{jt} \boldsymbol{\varrho}_{jt}$, $\boldsymbol{\tau}_t \equiv \sum_j \omega_{jt} \boldsymbol{\tau}_{jt}$, $\boldsymbol{\nabla}_t \equiv \sum_j \omega_{jt} \boldsymbol{\nabla}_{jt}$*, and* $\boldsymbol{\pi}_t \equiv \sum_j \omega_{jt} \boldsymbol{\pi}_{jt}$.

**Proof.** Follows immediately from Proposition 1. ■

Lemma 2 operationalizes Proposition 1 at the aggregate level. It shows that the cumulative divergence between the measured aggregate return on capital and the risk-free rate can be exactly decomposed into the capital-weighted cumulative contributions of each component identified in the proposition. The aggregate divergence therefore inherits the same economic structure as the firm-level decomposition. At the same time, it highlights an additional channel through which the aggregate gap can evolve: changes in the distribution of capital across firms. Even if firm-level components remain unchanged, shifts in capital across firms can affect the aggregate divergence.

Two implications follow. First, the decomposition can be implemented directly in the data using capital-weighted aggregates of the firm-level components. Second, expressing the decomposition in cumulative differences implies that identifying cumulative movements in the data is as informative as identifying levels, which is convenient in the empirical application.

The lemma therefore links the firm-level decomposition to the aggregate divergence of interest, allowing the contribution of each economic force to be quantified and enabling aggregate counterfactual exercises.

## 3.5 Model-Driven Identification

Having presented the main theoretical results of the model, we now show how its structure gives rise to a constructive identification strategy for each firm-level object of interest. We defer the practical details of implementation to Section 4.

**Directly measurable objects.** Risk-free rates $r_{t-1}$, depreciation rates $\delta_{jt}$, capital gains $\boldsymbol{\varrho}_{jt}$, and taxes $\boldsymbol{\tau}_{jt}$ can be measured from standard data sources. Given the output elasticities $\mathcal{E}_k$ and $\mathcal{E}_\ell$, revenue-based marginal products can be computed directly from their definitions, and markups can in principle be measured from Equation (7).[12] This leaves two objects to be identified: risk premia $\boldsymbol{\zeta}_{jt}$ and capital wedges $\boldsymbol{\nabla}_{jt}$.

**Risk premia.** Corollary 1 shows that variation in the adjusted revenue-based marginal product of capital alone identifies at most the joint contribution of risk premia and capital wedges to the user cost of capital. To separately recover these two objects, we exploit the asset-pricing structure embedded in Lemma 1. In particular, the lemma implies that risk premia satisfy the standard covariance representation of asset pricing (e.g., Cochrane, 2009), whereby a firm's risk premium equals the product of its exposure to aggregate risk and the aggregate price of risk. This covariance restriction provides the additional identifying restriction needed to disentangle risk premia from capital wedges within the generalized user cost of capital.

Our empirical implementation follows the canonical two-pass procedure dating back to Fama and MacBeth (1973). In practice, given a state-of-the-art measure of the stochastic discount factor $M_t$—described in detail in Section 4.2.2—firm-level risk premia can be estimated using a two-stage procedure. The first step involves estimating $\boldsymbol{\beta}_{jt}$, which captures a firm's exposure to movements in the stochastic discount factor. As shown in Lemma 1, this exposure is defined as the covariance between $\mathcal{R}_{jt}^{\nabla}$ and $M_t$ divided by the variance of $M_t$, or equivalently, as the population OLS coefficient from a regression of $\mathcal{R}_{jt}^{\nabla}$ on $M_t$. This coefficient can therefore be estimated using the following firm-specific regression:

$$\mathcal{R}_{jt}^{\nabla} = \alpha_{j\tau} + \boldsymbol{\beta}_{j\tau} M_t + \nu_{jt}, \tag{22}$$

[12] We discuss the estimation of the output elasticity of inputs in Section 4.2.1 when describing the empirical implementation of our approach.

which can be implemented using backward-looking rolling windows of $N_\tau$ years—i.e., for each year $\tau$, data from the period $t \in [\tau - N_\tau, \tau]$ are used.

In the second stage, given the time-varying firm-level estimate $\boldsymbol{\beta}_{jt}$, we estimate the aggregate price of risk $\boldsymbol{\lambda}_t$ using Equation (12). In practice, this involves estimating the following cross-sectional regression for each year:

$$\mathcal{R}_{jt}^{\nabla} - r_{t-1} = \boldsymbol{\beta}_{jt}\boldsymbol{\lambda}_t + \boldsymbol{\nabla}_{jt}, \tag{23}$$

where $\boldsymbol{\nabla}_{jt}$ is naturally treated as a residual, since by definition it captures variation in revenue-based marginal returns on capital that is unrelated to all other variables. Finally, the time-varying firm-level risk premium is measured as $\boldsymbol{\zeta}_{jt} = \boldsymbol{\beta}_{jt}\boldsymbol{\lambda}_t$.

**Capital wedges.** Once the other components in Equation (23) are accounted for, the capital wedge is recovered as the residual, as in the misallocation literature.

# 4 Data, Variable Construction, and Measurement

This section presents the data sources used for the empirical analysis, defines each empirical variable, and describes the measurement of the fundamental objects underlying our theory.

## 4.1 Data Sources and Variable Construction

In this section, we briefly describe the main data sources and the construction of the key variables used in the empirical analysis. Appendix B provides additional details on the data cleaning procedures and summary statistics for the main variables.

**Firm-level data.** The primary data source is Compustat, a firm-level database providing balance sheet information for publicly traded U.S. firms. Compustat is well suited for our purposes for three reasons. First, its broad coverage across sectors and years enables a comprehensive historical analysis of capital returns. Second, its extensive use in the literature ensures direct comparability between our estimates and existing evidence. Third, although publicly traded firms represent only a small fraction of firms by count, the highly right-skewed distribution of capital implies that they account for a large share of aggregate capital (Crouzet and Mehrotra, 2020). Consistent with this, we estimate that publicly traded firms account for roughly 60 percent of total non-residential capital in the United States. Compustat therefore provides a natural population for studying the aggregate dynamics of the return on capital.

**GDP and investment deflators.** Price deflators for GDP and investment components are from NIPA Table 1.1.9, while capital stocks for each investment component are from FAT Table 4.1. Following Gourio et al. (2022), we construct the investment deflator $P_t^K$ as a Törnqvist chain-weighted price index: $P_t^K = \exp\left(\sum_{\tau=t_0+1}^{t} \Delta \ln P_\tau^K\right)$, where $t_0$ denotes the base year, $\Delta \ln P_t^K = \sum_a \frac{1}{2}\left(\frac{K_{at}}{\sum_a K_{at}} + \frac{K_{at-1}}{\sum_a K_{at-1}}\right) \Delta \ln P_{at}$, $P_{at}$ is the price deflator of asset type $a$, and $K_{at}$ is the aggregate capital stock of asset type $a$. The index is normalized to unity in 2017. The relative price of investment is $Q_t = P_t^K / P_t^{GDP}$, where $P_t^{GDP}$ is the GDP deflator. Appendix B.3 compares the evolution of the Törnqvist chain-weighted investment deflator and the national accounts investment deflator.

**Output, inputs, and capital measures.** We use sales, $\texttt{sale}_{jt}/P_t^{GDP}$, to measure firm revenues, cost of goods sold, $\texttt{cogs}_{it}/P_t^{GDP}$, to capture variable input, and the non-capitalized fraction of selling, general, and administrative expenses, $(1-\gamma_{s(i)}^{ORG})(\texttt{xsga}_{jt} - \texttt{xrd}_{jt})/P_t^{GDP}$, to measure overhead costs.

Tangible capital is constructed using the perpetual inventory method: $k_{jt}^T = (1 - \delta^T)k_{jt-1}^T + x_{jt}^T$, where $\delta^T = 0.07$, $x_{jt}^T - \delta^T k_{jt-1}^T \equiv \left(\texttt{ppent}_{jt} - \texttt{ppent}_{jt-1}\right)/P_t^K$, and $k_{j0}^T = \texttt{ppegt}_{j0}/P_0^K$.

We measure intangible capital stock as the sum of three components, following best practices in corporate finance (Peters and Taylor, 2017; Ewens et al., 2024). The first component, knowledge capital, is capitalized R&D, defined as: $k_{jt}^{KNWL} = (1-\delta_{s(j)}^{KNWL})k_{jt-1}^{KNWL} + \texttt{xrd}_{jt}/P_t^K$, where sector-level depreciation rates, $\delta_{s(j)}^{KNWL}$, are from Ewens et al. (2024), and $k_{j0}^{KNWL} = 0$. The second component, organizational capital, is constructed by capitalizing a portion of selling, general, and administrative expenses as follows: $k_{jt}^{ORG} = (1 - \delta^{ORG})k_{jt-1}^{ORG} + \gamma_{s(j)}(\texttt{xsga}_{jt} - \texttt{xrd}_{jt})/P_t^K$, where $\gamma_{s(j)}^{ORG}$ is from Ewens et al. (2024), $\delta^{ORG} = 0.20$, and $k_{j0}^{ORG} = 0$, and values are deflated using the appropriate investment deflator. Appendix C.1 shows that our results are robust to alternative initial conditions for $k_{j0}^{KNWL}$ and $k_{j0}^{ORG}$. The third component, the gross balance sheet intangible capital net of goodwill, is defined as: $k_{jt}^{BS} = (\texttt{intan}_{jt} - \texttt{gdwl}_{jt} + \texttt{am}_{jt})/P_t^K$.[13] Total intangible capital is calculated as: $k_{jt}^I = k_{jt}^{KNWL} + k_{jt}^{ORG} + k_{jt}^{BS}$.

Thus, the firm-level total capital stock and depreciation rate are defined as follows:

[13]This component is crucial to include, as it typically accounts for most software on the balance sheet, which is the fastest-growing segment of aggregate intangible capital according to BEA data. For a detailed discussion on software accounting standards, see Chiavari and Goraya (2025) and Aum and Shin (2024).

$k_{jt} = k_{jt}^T + k_{jt}^I$, and $\delta_{jt} = \frac{k_{jt}^T}{k_{jt}}\delta^T + \frac{k_{jt}^I}{k_{jt}}\delta^I$, with $\delta^I \equiv \sum_{jt}\frac{1}{T}\left(\frac{k_{jt}^{KNWL}}{k_{jt}^I}\delta_{s(j)}^{KNWL} + \frac{k_{jt}^{ORG}}{k_{jt}^I}0.20 + \frac{k_{jt}^{BS}}{k_{jt}^I}0.20\right)$, where $T$ is firm-year observations. Appendix B.4 shows the evolution of the distribution of firm-level depreciation rates over time.

**Corporate taxation.** Statutory corporate income tax rates $\tau_t^c$ are obtained from historical IRS publications. The corporate tax treatment of capital varies across asset types. Tangible capital $k_{jt}^T$ and balance sheet intangible capital $k_{jt}^{BS}$ are treated symmetrically, subject to partial historical-cost depreciation allowances and investment deductibility. By contrast, expensed intangible capital $k_{jt}^{KNWL} + k_{jt}^{ORG}$ cannot be amortized and is fully deductible upon investment (Cloyne et al., 2022).

Total deducible depreciation is thus defined as just a function of observables and measured as follows:

$$\delta_{k,jt}k_{jt} = \delta^T k_{jt}^T + \delta^I k_{jt}^{BS}. \tag{24}$$

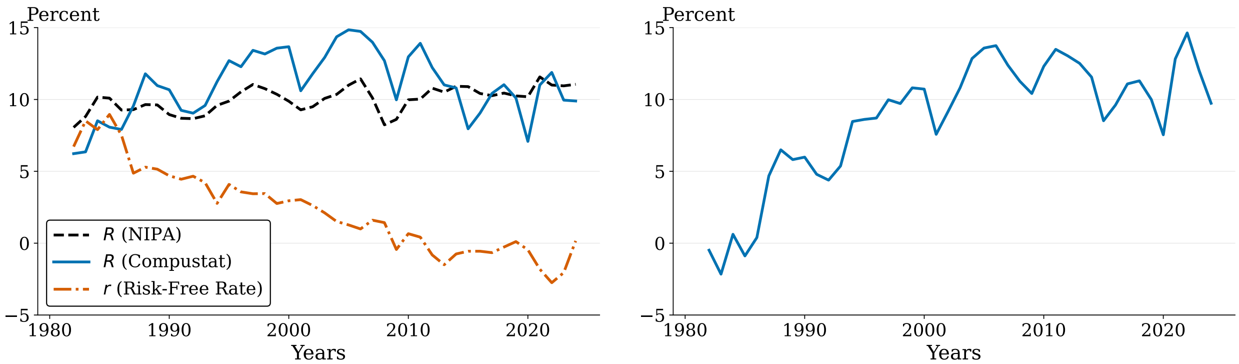
Total deductible investment is defined as follows:

$$\delta_{x,jt}x_{jt} = \delta_{x,t}(x_{jt}^T + x_{jt}^{BS}) + x_{jt}^{KNWL} + x_{jt}^{ORG}, \tag{25}$$

where, $x_{jt} \equiv x_{jt}^T + x_{jt}^{BS} + x_{jt}^{KNWL} + x_{jt}^{ORG}$ is total investment and $x_{jt}^{BS} \equiv k_{jt}^{BS} - (1-0.20)k_{jt-1}^{BS}$ is balance sheet intangible investment. where, $x_{jt} \equiv x_{jt}^T + x_{jt}^{BS} + x_{jt}^{KNWL} + x_{jt}^{ORG}$ is total investment and $x_{jt}^{BS} \equiv k_{jt}^{BS} - (1-0.20)k_{jt-1}^{BS}$ is balance sheet intangible investment. The parameter $\delta_{x,t}$ denotes aggregate effective investment deductibility and is set to 0.2, following Atkeson et al. (2024). Appendix B.5 shows that this choice closely matches the share of aggregate corporate tax revenues accounted for by firms in our Compustat sample to independent estimates for publicly traded C corporations and aligns the model-implied effective corporate tax rate with the historical estimates of Gravelle (2006). Appendix B.5 also reports the joint evolution of deductible depreciation, deductible investment, and statutory corporate tax rates over time.

**Comparing aggregate returns: national accounts vs. Compustat.** Before turning to the measurement of each component making the measured aggregate return on capital, we assess whether Compustat provides a suitable laboratory for studying the aggregate divergence between this measure and the risk-free rate. To do so, we construct the measured firm-level return on capital using Equation (13) and aggregate it according to Equation (20) to obtain the Compustat counterpart of the measured aggregate return on capital introduced in Section 2.

**Figure 2:** Measured Aggregate Return on Capital: National Accounts vs. Compustat




**(a)** Return on Capital and Risk-Free Rate

**(b)** Return Gap

*Note.* Panel (a) compares the aggregate return on capital from Compustat, constructed as described in the text, with its national accounts counterpart and the risk-free rate, both from Section 2. Panel (b) shows the gap between the Compustat measure of the aggregate return and the risk-free rate.

Panel (a) in Figure 2 shows that the aggregate return on capital constructed from Compustat closely tracks its national accounts counterpart over time. This alignment reflects the highly right-skewed distribution of capital across firms, whereby large firms—those represented in Compustat—account for the bulk of aggregate capital and its dynamics. Panel (b) in Figure 2 shows that the return gap in Compustat closely mirrors its aggregate counterpart, rising from near zero in the early 1980s to approximately 10 percentage points by the end of the sample.

Taken together, these results indicate that Compustat provides a natural quantitative laboratory for studying the firm-level origins of the divergence between the aggregate return on capital and the risk-free rate.

## 4.2 Measurement and Evolution of the Aggregate Return Components

### 4.2.1 Capital Gains and Corporate Taxation

We measure the capital gains and corporate taxation components of our decomposition using their definitions in Lemma 1 together with the variables constructed in Section 4.1. Panels (a) and (b) of Figure 3 plot the evolution of their capital-weighted averages over time. Both components display substantial short-run volatility but no pronounced secular trend over the sample period, consistent with Gomme et al. (2011).

Capital gains fluctuate with movements in investment prices but remain close to zero on average. The taxation component primarily reflects changes in effective corporate tax rates. Because effective corporate tax rates declined over the sample period, the level of

**Figure 3:** The Components of the Measured Return on Capital over Time


**(a)** Capital Gains

**(b)** Corporate Taxation

**(c)** Pure Profit Rate

**(d)** Risk Premium

**(e)** Capital Wedge

*Note.* The figure plots the evolution of the main components of the measured return on capital between 1982 and 2024. Panels (a)-(e) report the capital-weighted aggregates of capital gains, taxation, pure profit rates, risk premia, and capital wedges, respectively.

the taxation component is negative, with pronounced declines around the Tax Reform Act of 1986 and the Tax Cuts and Jobs Act of 2017.

Appendix B.6 reports the cross-sectional distributions of both components, while Appendix C.1 shows that the evolution of the trends presented here are robust to alternative investment deflators and alternative calibrations of investment deductibility, $\delta_{x,t}$.

#### 4.2.2 Profit Rates

This section describes how we measure firm-level profit rates and discusses the identification of the underlying markups and production function elasticities.

**Markups and production function estimation: challenges and solutions.** We measure firm-level markups using the ratio estimator in Equation (7), following De Loecker and Warzynski (2012). This approach recovers markups as the ratio of the output elasticity of the variable input, which must be estimated from firm-level production functions, to the variable input costs as the share of revenue that is directly observed in the data. Appendix B.7 shows that the accounting-based markup measure proposed by Baqaee and Farhi (2020), which does not require production function estimation, yields markup trends that are similar to those obtained using the baseline estimator presented in this section.

Two identification challenges arise in estimating gross output production function elasticities from firm-level revenue data. The first arises under imperfect competition when output is measured using revenues rather than physical quantities (Klette and Griliches, 1996). In this case, empirical implementations typically recover revenue elasticities, whereas markup estimation requires output elasticities. Bond et al. (2021) show that substituting the former for the latter can render the ratio estimator uninformative about markup levels. More generally, De Ridder et al. (2024) show that revenue-based approaches remain informative primarily about dispersion and time-series variation in markups rather than their levels. Consistent with these identification results, our analysis focuses on cumulative changes over time rather than levels, aligning the empirical implementation with the theoretical decomposition in Lemma 2.

A second challenge is that gross output production functions are not generally identified without additional sources of variation, even under perfect competition (Flynn et al., 2019; Gandhi et al., 2020). To address the challenges associated with gross output production functions and revenue-based data, we build on recent advances that incorporate imperfect competition directly into production function estimation. Ackerberg and De Loecker (2024, 2026) show that, under structured models of competition such as Cournot or Bertrand-Nash with (nested) logit demand, variation in the competitive environment provides sufficient statistics for unobserved demand shocks and markups. Exploiting variation in competitors' revenues to construct *oligopoly instruments* restores identification of production function elasticities in revenue-based settings and provides the additional exogenous variation required to identify gross output production functions.[14]

With these oligopoly instruments in hand, we implement the first stage of the control-function approach and embed it in a system GMM framework using the moment conditions of Blundell and Bond (1998), which accommodate firm-level fixed effects in productivity. Implementation details of the baseline estimator, together with the resulting elasticities and markups, are reported in Appendix B.7. In line with De Loecker et al. (2020) and Chiavari (2025), we find a modest decline in the elasticities of variable inputs, accompanied by a gradual increase in the elasticity of capital and in returns to scale. Consistent with the broader evidence reviewed by Syverson (2024), we also find a sustained rise in markups.

We evaluate the robustness of these findings along several dimensions. First, we implement dynamic panel estimators that avoid the first-stage inversion in the baseline specification, addressing the concerns emphasized by Bond et al. (2021). Second, we replace our baseline moment conditions with those proposed by Ackerberg et al. (2015), widely used in the structural IO literature. Third, we explicitly account for measurement error in capital following Collard-Wexler and De Loecker (2021) and consider alternative initial conditions for the perpetual-inventory construction of intangible capital. Appendix B.7 shows that across all specifications the implied evolution of output elasticities and markups remains close to our baseline estimates, indicating that the main findings are not driven by a particular production function estimator or identification strategy.

**Profit rates.** Given estimates of production function elasticities and markups, we construct firm-level pure profit rates using their definition in Proposition 1. Panel (c) of Figure 3 reports the capital-weighted evolution of this measure, while Appendix B.7 presents the evolution of the entire distribution. The profit rate seems to rise from the early 1980s into the mid-1990s, then decline through much of the 2000s and 2010s before rebounding recently.

While our estimates display a rise in profits consistent with the recent literature, the magnitude is more muted and the time-series pattern differs from the seminal findings in

[14]Effectively, while the model in Section 3 allows for a general competitive environment subject only to downward-sloping demand, data limitations require the empirical analysis to specialize to a class of demand systems admitting such sufficient statistics.

De Loecker et al. (2020). This difference does not reflect discrepancies in the underlying data or in the estimation of production functions and markups. Rather, it arises from how the user cost of capital is measured, as shown formally in Appendix B.7.3 through an exact decomposition.

Much of the literature builds on the Hall and Jorgenson (1967) framework, in which the user cost is approximated by the sum of the risk-free rate, depreciation, and a risk premium. Lemma 1 shows that this formulation is incomplete in the presence of taxes, capital gains, and wedges. In our framework, the user cost is equal to the adjusted revenue-based marginal product of capital and extends the standard formulation to incorporate these additional components.

Empirically, the revenue-based marginal product of capital remains broadly stable over time, and above the declining user cost implied by the Hall and Jorgenson (1967) formula for much of the sample, consistent with the findings of Van Vlokhoven (2024). As a result, our generalized user cost is higher than typically measured in the literature (e.g., Barkai, 2020), mechanically reducing the residual attributed to profits. Appendix B.7.3 shows that this difference is primarily driven by the rise in the capital wedges, which we measure in Section 4.2.4.

#### 4.2.3 Risk Premia

We estimate firm-level risk premia using the identification strategy developed in Section 3.5. Following the empirical asset pricing literature since Fama and MacBeth (1973), observable risk factors are commonly used as empirical proxies for the stochastic discount factor, capturing the compensation investors require for bearing aggregate risk. Our baseline specification uses the investment-based five-factor model of Hou et al. (2015).[15] This model is well suited to our setting because it is designed to price cross-sectional differences in firm returns. Appendix B.8 provides implementation details for the estimation of firm-level risk premia. Commonly used alternatives—including the Fama and French (2023) five-, three-, and one-factor models, as well as the consumption CAPM—yield a quantitatively similar time series for the capital-weighted mean risk premium, as shown also in Appendix B.8.

Panel (d) of Figure 3 reports the evolution of the capital-weighted mean, while Appendix B.8 presents the evolution of the entire distribution. Risk premia are, on average,

[15] The factors comprise: (i) the market return; (ii) a size factor (long small, short large firms); (iii) an investment factor (long low-investment, short high-investment firms); (iv) a profitability factor (long high–return-on-equity, short low–return-on-equity firms); and (v) an expected investment factor (long firms with high expected one-year-ahead investment-to-assets changes, short those with low expected changes). The data are available at available at global-q.org.

close to zero and have remained broadly stable over the past four decades. At the same time, they exhibit substantial short-run volatility, with the largest fluctuations occurring around major changes in corporate taxation.

Appendix B.8 provides a series of validations of the estimated risk premia. Firms with higher estimated risk premia exhibit higher returns on equity, lower capital stocks, and lower capital-to-variable-cost ratios, consistent with the theoretical predictions of the model. In addition, consistent with David et al. (2022), sectors with more dispersed risk premia also display greater dispersion in revenue-based marginal products of capital and revenue total factor productivity.

Our estimates are consistent with the broader asset-pricing evidence showing little long-run trend in aggregate risk premia. In line with our findings, a broad range of financial and macroeconomic risk indicators—including the VIX and SKEW indices, short-term funding spreads (Drechsler et al., 2018), credit spreads (Gilchrist and Zakrajšek, 2012; Jordà et al., 2019), and measures of policy and macroeconomic uncertainty (Baker et al., 2016; Jurado et al., 2015)—exhibit little evidence of a major secular increase. Estimates of the aggregate equity risk premium similarly display limited long-run variation (see Duarte and Rosa, 2015 for a review).[16]

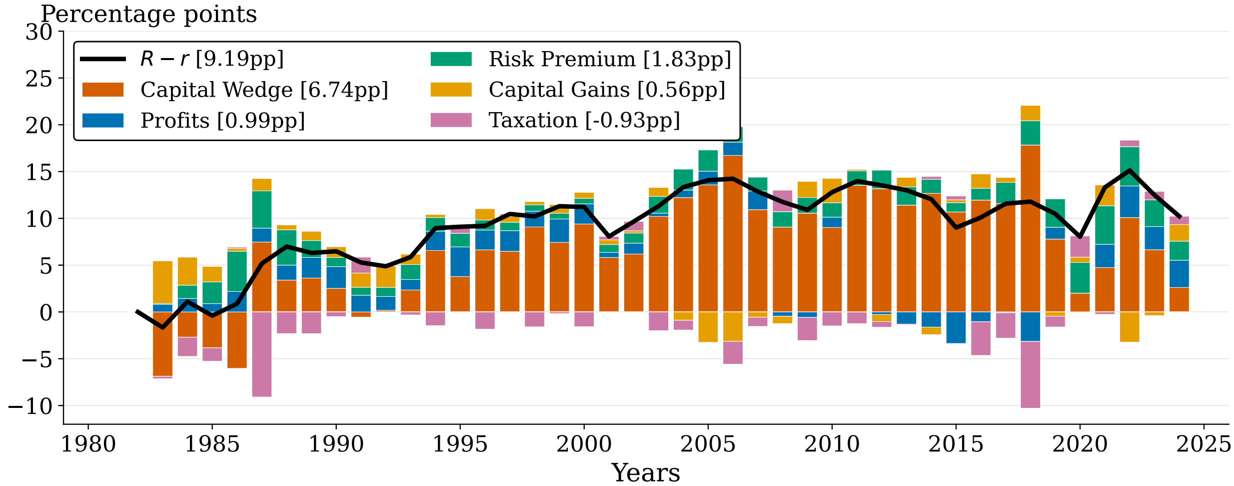
At the same time, a handful of influential macroeconomic studies have documented an increase in the risk premium since the 2000s (e.g., Farhi and Gourio, 2018), with estimated increases on the order of 2 percentage points. Our estimates are broadly consistent with this evidence. While the average risk premium remains relatively stable over the long run, we find a similar upward trend beginning in the early 2000s and a somewhat more pronounced increase in recent years.

#### 4.2.4 Capital Wedges

We now measure capital wedges using the residual-based approach described in Section 3.5. Panel (e) of Figure 3 reports the time series of capital-weighted mean, while Appendix B.9 presents the evolution of the entire distribution. The figure reveals a pronounced rise in the capital wedge over the sample period. The capital-weighted mean increases steadily through the 2000s, peaks at roughly 15 percentage points during 2007–2018, and subsequently declines, remaining approximately 5 percentage points above its initial level at the end of the sample.

[16] For a link between the equity risk premium and the return-on-capital risk premium, see David et al. (2022). Other papers showing no increase in the aggregate equity risk premium include Avdis and Wachter (2017), Campbell and Thompson (2008), Gagliardini et al. (2016), Gormsen and Huber (2023), Jagannathan et al. (2001), Lettau et al. (2008), and Martin (2017).

**Figure 4:** The Anatomy of the Return on Capital and Risk-Free Rate Gap




*Note.* The figure plots the cumulative evolution of the gap between the measured aggregate return on capital and the risk-free rate, together with the cumulative contributions of capital wedges, profits, risk premia, capital gains, and corporate taxation. Legend entries report average contributions over the period 1982-2024.

Because capital wedges are measured residually, part of their variation may reflect measurement error. To assess this possibility, Appendix B.9 implements the correction procedure proposed by Bils et al. (2021). Consistent with their findings, we estimate that measurement error has increased over time. Quantitatively, however, the magnitude of this increase is far too small to account for the rise in capital wedges observed in the data. We therefore conclude that changes in measurement error are unlikely to be the primary driver of the observed increase in capital wedges and defer the discussion of alternative explanations for this rise to Section 5.4.

# 5 The Firm-Level Anatomy of the Divergence

This section implements the decomposition developed in Section 3 using the firm-level measurements constructed in Section 4. We show that the secular divergence between the measured aggregate return on capital and the risk-free rate is driven predominantly by a sustained rise in capital wedges. We then show that this pattern originates at the firm level and trace it to a weakening capital response during episodes of firm expansion, which we link to the rise of intangible capital and changes in corporate discount rates.

## 5.1 The Macroeconomic Drivers

Figure 4 decomposes the gap between the measured aggregate return on capital and the risk-free rate into the components described in Lemma 2, using the firm-level measures developed in the previous section.

The dominant contribution comes from aggregate capital wedges, which account on average for 6.74 percentage points of the 9.19 percentage point rise in the return gap over the sample period. Risk premia and profits contribute 1.83 and 0.99 percentage points, respectively, while capital gains and taxation contribute 0.56 and -0.93 percentage points. Taken together, these results point to capital wedges as the primary force behind the secular divergence between the measured return on capital and the risk-free rate.

While the limited role of capital gains and corporate taxation is consistent with earlier work (e.g., Gomme et al., 2011), we find a smaller contribution of profits and risk premia than studies such as Farhi and Gourio (2018). Two considerations help explain this difference. First, we study the evolution of the return gap since the 1980s rather than since the 2000s. Because the increase in the gap is substantially larger over this longer horizon, a similar post-2000 rise in risk premia accounts for a smaller fraction of the cumulative divergence. Second, we measure profits using the generalized economic cost of capital. As discussed in Section 4.2.2 and Appendix B.7.3, this broader user-cost measure implies a more modest increase in profit rates.

Appendix C.1 shows that these conclusions are not driven by the specific measurement choices adopted in the previous section. In particular, the results remain robust to alternative production function estimators, markup measures, intangible capital initial conditions, risk premia estimates, investment deflators, and calibrations of investment deductibility rates. The remainder of this section therefore focuses on uncovering the microeconomic origins of the rise in capital wedges.

## 5.2 The Rise in the Capital Wedge and The Role of Sectors and Firms

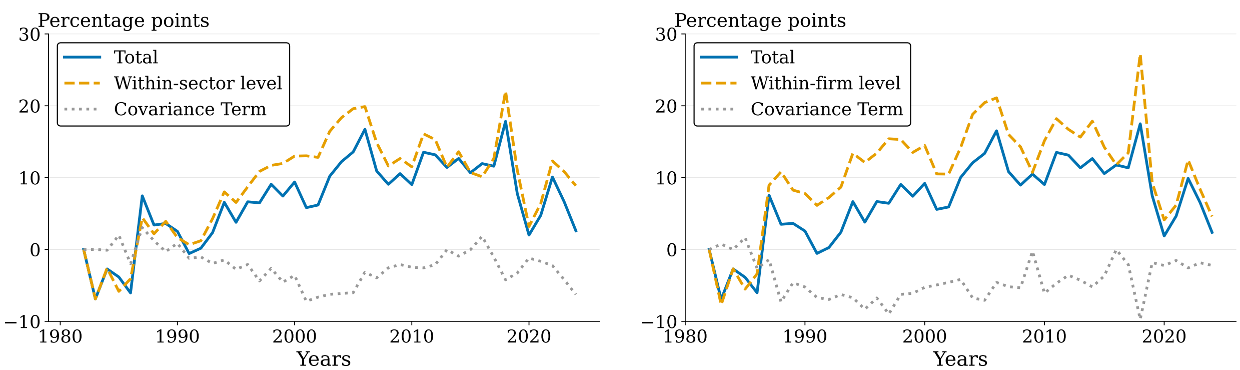
The previous section showed that the rise in aggregate capital wedges is the primary driver of the divergence of interest. However, it leaves open the question of where this increase originates. This section examines the extent to which changes in sectoral and firm-level composition contribute to the documented rise in aggregate capital wedges.

**The role of sectors.** To examine the role of sectors, we implement the following decomposition Olley and Pakes (1996) at the sector level:

$$\boldsymbol{\nabla}_t = \underbrace{\bar{\boldsymbol{\nabla}}_t^S}_{\substack{\text{Common}\\ \text{Effect}}} + \underbrace{\mathbb{C}ov(\omega_{st}, \boldsymbol{\nabla}_{st})}_{\substack{\text{Sectoral composition}\\ \text{Effect}}}\ , \tag{26}$$

where $\boldsymbol{\nabla}_t$ denotes the capital-weighted average capital wedge, $\bar{\boldsymbol{\nabla}}_t^S$ the unweighted average capital wedge across sectors, $\omega_{st} \equiv \sum_{j \in \mathcal{J}_t^s} \omega_{jt}$ capital shares at 2-digit NAICS sector, and $\boldsymbol{\nabla}_{st} \equiv \sum_{j \in \mathcal{J}_t^s} \frac{\omega_{jt}}{\sum_{j \in \mathcal{J}_t^s} \omega_{jt}} \boldsymbol{\nabla}_{it}$ sector-level capital wedges. The common effect captures changes in the unweighted average capital wedge, that is, changes that affect all or most sectors symmetrically. In contrast, the composition effect captures the covariance between capital shares and wedges at the sector-level, that is, changes in the joint distribution of these two objects. [17]

**Figure 5:** Olley-Pakes Decomposition at the Sector and Firm Level




**(a)** Sector-Level **(b)** Firm-Level

*Note.* The figure reports the Olley–Pakes decomposition of the aggregate capital wedge between 1982 and 2024. Panel (a) presents the sector-level decomposition, while Panel (b) presents the firm-level decomposition. In each panel, the aggregate capital wedge is decomposed into a common component, corresponding to the unweighted average wedge, and a composition component, corresponding to the covariance between capital shares and wedges. All series are expressed as cumulative deviations from their 1982 values, in percentage points.

Panel (a) in Figure 5 reports the evolution of these two components of Equation (26) together with the aggregate capital wedge. The rise in the aggregate capital wedge is accounted for almost entirely by the common effect, while changes in sectoral composition contribute little to its long-run evolution. These findings imply that the increase in capital

[17] Following the standard convention in the Olley and Pakes (1992) literature, $\text{Cov}(\omega_{st}, \nabla_{st})$ here denotes the cross-product term, $\sum(\omega_{st} - \bar{\omega}_t)(\nabla_{st} - \bar{\nabla}_t^S)$. We follow this convention throughout unless explicitly mentioned otherwise.

wedges does not primarily reflect a reallocation of economic activity toward sectors with persistently higher wedges. Instead, it occurs predominantly within sectors, suggesting that its underlying sources operate at a finer level of disaggregation, to which we now turn.

**The role of firms.** We begin by applying the decomposition from the previous section at the firm level:

$$\boldsymbol{\nabla}_t = \underbrace{\bar{\boldsymbol{\nabla}}_t^F}_{\substack{\text{Common}\\ \text{Effect}}} + \underbrace{\mathbb{C}ov(\omega_{jt}, \boldsymbol{\nabla}_{jt})}_{\substack{\text{Firm composition}\\ \text{Effect}}}, \tag{27}$$

where $\boldsymbol{\nabla}_t$ still denotes the capital-weighted average capital wedge, $\bar{\boldsymbol{\nabla}}_t^F$ now denotes the unweighted average capital wedge across firms, $\omega_{jt}$ capital shares, and $\boldsymbol{\nabla}_{jt}$ firm-level capital wedges. The common and composition effects capture the same forces as in the previous decomposition, but now applied at the firm level.

Panel (b) in Figure 5 presents the evolution of the different components of the firm-level decomposition in Equation (27). As in the sector-level analysis, the rise in the aggregate capital wedge is driven primarily by the common-effect component, while the composition-effect component contributes negatively. Taken together, these findings suggest that the rise in capital wedges reflects broad changes in firm-level behavior rather than compositional shifts across firms or sectors.

Motivated by this evidence, the next section studies the firm-level dynamics around changes in capital wedges to shed further light on the underlying forces driving this phenomenon.

## 5.3 Firm Dynamics and Capital Wedges

To study the firm-level dynamics underlying the rise in capital wedges, we construct capital wedge quasi-shocks following the approach of Hamilton (2018), applied at the firm level. Specifically, we regress capital wedges on their own lags and define the capital wedge quasi-shock, $\varepsilon_{jt}^{\boldsymbol{\nabla}}$, as the corresponding innovation:

$$\boldsymbol{\nabla}_{jt} = \alpha + \sum_{\ell=1}^{\mathcal{L}} \beta_\ell \boldsymbol{\nabla}_{jt-\ell} + \varepsilon_{jt}^{\boldsymbol{\nabla}}, \tag{28}$$

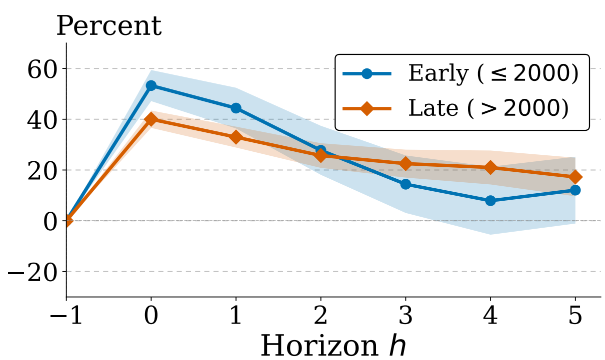
and we set the lags to $\mathcal{L} = 5$. We refer to $\varepsilon_{jt}^{\boldsymbol{\nabla}}$ as a capital wedge quasi-shock because its purpose is simply to isolate, in a descriptive sense, movements in capital wedges relative to a firm's own past dynamics, without imposing any causal or exogeneity interpretation.

We then use these quasi-shocks to estimate local linear projections following Jordà (2005). Specifically, for each horizon $h = 0, \ldots, 5$, we estimate:

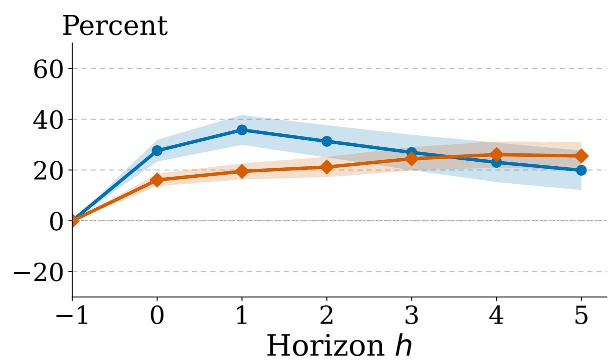
$$y_{jt+h} - y_{jt-1} = \alpha_h + \beta_h \varepsilon_{jt}^{\nabla} + \boldsymbol{x}_{jt}' \theta_{jt+h} + \gamma_j + \gamma_{st} + \epsilon_{jt}, \tag{29}$$

where $y_{jt}$ denotes the outcome variable of interest, $\varepsilon_{jt}^{\nabla}$ is the capital wedge quasi-shock, and $\beta_h$ captures the dynamic response at horizon $h$, which we interpret as an impulse response function. The vector $\boldsymbol{x}_{jt}$ includes controls such as lags of the quasi-shock and lags of the growth rate of the dependent variable. We include firm fixed effects, $\gamma_j$, and sector-by-time fixed effects, $\gamma_{st}$, and cluster standard errors at the firm level. Any persistent firm-level heterogeneity is absorbed by firm fixed effects, so that $\beta_h$ is identified from within-firm variation in the quasi-shock only.

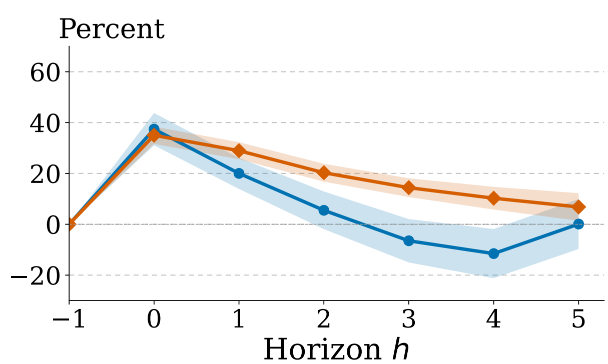
**Figure 6:** Dynamics Around Capital Wedge Quasi-Shocks




**(a)** Sales




**(b)** Capital




**(c)** MRPK

*Note.* The figure reports local projection impulse responses of sales (Panel (a)), capital (Panel (b)), and the revenue-based marginal product of capital (Panel (c)) following a 1 unit rise in firm-level capital wedge quasi-shock. Responses are estimated separately for the pre-2000 and post-2000 periods. The horizontal axis reports years relative to the shock. Variables are expressed in log deviations, except for the revenue-based marginal product of capital, which is expressed in percentage points. Shaded areas denote 95% confidence intervals.

Figure 6 plots the impulse response functions of sales, capital, and the revenue-based marginal product of capital following a capital wedge quasi-shock, separately for the periods before and after 2000. In both subsamples, quasi-shock episodes are characterized by large and persistent increases in sales accompanied by a slower and more gradual buildup in capital. Together, these dynamics generate a persistent increase in the revenue-based marginal product of capital and, consequently, in the return on capital.

However, important differences emerge across periods. Relative to the pre-2000 sample, the post-2000 period exhibits a markedly slower capital accumulation response around these episodes, despite only a modest attenuation in the increase in sales. As a result, the revenue-based marginal product of capital remains persistently higher in the later period. These changing dynamics provide a potential explanation for the substantially higher return on capital observed in the second half of the sample and are consistent with the rise in firm-level capital wedges and the decline in the covariance between wedges and firms' relative capital shares highlighted by the decomposition in Equation (27).[18]

More broadly, these patterns are consistent with the literature on the rise of superstar firms (e.g., Autor et al., 2020; De Loecker et al., 2020; Kehrig and Vincent, 2021) and the decline in firm-level responsiveness (e.g., Decker et al., 2020), which documents persistent episodes of rapid sales growth without commensurate increases in inputs.

Before turning to potential explanations for the patterns documented in Figure 6, we present a series of case studies that provide a more concrete illustration of these episodes. Additional details on each case study are provided in Appendix C.2.

- *The case of NVIDIA (2023).* Following the diffusion of generative AI after the release of ChatGPT in late 2022, demand for AI compute increased sharply, leading growth of NVIDIA GPU purchases at unprecedented rates. NVIDIA's revenues rose dramatically, while its capital stock increased comparatively little (see Figure C.2 in Appendix C.2). This divergence reflects, at least in part, the intangible-intensive nature of NVIDIA's business model: scaling AI-related activity required relatively limited expansion in physical production capacity, but did involve additional investment in accumulation of software, platform, and developer ecosystems.[19]

[18] Appendix C.2 shows that capital wedges themselves exhibit dynamics consistent with the decomposition in Equation (27), despite the mechanically sharper responses induced by the quasi-shock construction.

[19] NVIDIA 2024 Form 10-K, "In fiscal year 2024, we launched the NVIDIA DGX Cloud, an AI-training-as-a-service platform which includes cloud-based infrastructure and software for AI, customizable pretrained AI models, and access to NVIDIA experts" and "CUDA includes hundreds of domain-specific libraries, SDKs, AI models and applications," highlighting continued expansion of proprietary software ecosystems and AI platform services rather than owned physical production capacity (see, NVIDIA Corporation, Form 10-K, fiscal year ending January 28, 2024).

- *The case of EOG Resources, Inc. (2003).* EOG is one of the largest independent crude oil and natural gas producers in the United States. In the early 2000s, it benefited from rising natural gas prices and the shale gas boom, of which it was a pioneer. This led to a substantial increase in revenues that was not matched by a comparable expansion in capital (see Figure C.3 in Appendix C.2). At least in part, this reflected management's stated objective of maximizing returns on capital by tightly controlling capital expenditures and limiting investment.[20]

- *The case of Devon Energy (1992).* Devon Energy is a U.S. independent energy company that experienced substantial and persistent sales growth in the early 1990s, associated with a series of acquisitions and the resulting expansion of its asset base. Unlike the post-2000 episodes discussed above, this increase in sales was accompanied by a comparable rise in capital accumulation (see Figure C.4 in Appendix C.2). As such, the case illustrates the pre-2000 environment in which periods of rapid firm growth were more closely associated with investment and capital accumulation as a growth strategy, implying a more limited increase in capital wedges.[21]

Overall, these case studies provide concrete illustrations of the dynamics documented in this section. While only suggestive, they are consistent with a shift from an environment in which firm growth was closely associated with capital accumulation to one in which sales growth increasingly outpaces investment. The examples point to the growing importance of intangible capital and changes in firms' investment selection criteria as plausible contributors to this transition. We examine these channels more systematically in the next section.

### 5.4 Behind the Changing Dynamics of Firms' Capital Accumulation

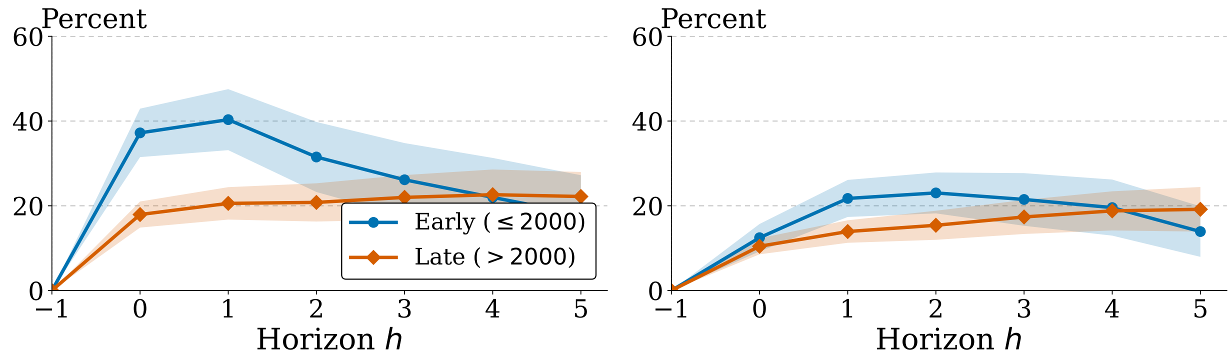
We now turn to empirically exploring the drivers of the capital wedge dynamics documented in the previous section. Our results point to an important role for intangible capital and rising required return premia, consistent with the broader literature and with the suggestive evidence from the case studies presented above.

[20] EOG's 2003 Form 10-K states that "EOG's business strategy is to maximize the rate of return on investment of capital by controlling all operating and capital costs. This strategy is intended to enhance the generation of cash flow and earnings from each unit of production on a cost-effective basis." See EOG Resources, Inc., Form 10-K, fiscal year ended December 31, 2003.

[21] Devon's 1995 Form 10-K characterizes the firm's strategy as "a two-pronged strategy of acquiring producing properties and engaging primarily in development drilling and limited exploration activities," under which growth was achieved largely through the acquisition and development of capital assets. See Devon Energy Corporation, Form 10-K, fiscal year ended December 31, 1995.

**Rising intangible capital.** Since the 1980s, intangible capital has risen dramatically in the broader economy (Corrado et al., 2009). Consistent with this trend, in Compustat intangible capital increased from roughly 35% of the total firm-level capital stock in 1982 to about 55% by 2024, as shown in Figure C.5 in Appendix C.3.

**Figure 7:** The Evolution of Tangible and Intangible Capital over Time




**(a)** Tangible Capital

**(b)** Intangible Capital

*Note.* The figure reports local projection impulse responses of tangible and intangible capital following a firm-level capital wedge quasi-shock. Responses are estimated separately for the pre-2000 and post-2000 periods. The horizontal axis reports years relative to the shock, and all variables are expressed in log deviations. Shaded areas denote 95% confidence intervals.

Figure 7 shows the evolution of tangible and intangible capital around capital wedge quasi-shocks. Three patterns stand out. First, both types of capital accumulate gradually around these episodes, consistent with the dynamics of total capital documented in the previous section. Second, intangible capital adjusts substantially more slowly than tangible capital across both subsamples. Third, the speed of adjustment of both forms of capital has declined over time.

These patterns raise the question of whether the growing importance of intangible capital—combined with its lower responsiveness—can account for the declining responsiveness of total capital. To assess this mechanism, Appendix C.3 applies a simple shift-share decomposition of the dynamics of total capital. We find that the rising share of intangible capital, together with the decline in its responsiveness over time, accounts for at least 40% of the decline in total capital responsiveness documented in Panel (b) in Figure 6. This estimate is likely conservative. In equilibrium, complementarities between tangible and intangible capital, as well as tighter financing constraints for intangible-intensive firms, may also contribute to the decline in the responsiveness of tangible capital shown in Panel (a) in Figure 7.

The NVIDIA and Devon case studies presented in the previous section provide concrete illustrations of the mechanisms discussed here. NVIDIA exemplifies the post-2000 environment, in which rapid revenue growth is accompanied by relatively weak capital accumulation and a greater reliance on intangible capital. By contrast, Devon illustrates the pre-2000 period, when capital accumulation was strongly associated with growth opportunities and firms' expansion was more tangible capital intensive.

Overall, these findings are consistent with the broader literature arguing that intangible capital is inherently more frictional than tangible capital, both because it is less collateralizable (e.g., Ai et al., 2020; Caggese and Pérez-Orive, 2022; Falato et al., 2022; Zhang, 2024) and because it is subject to greater reallocation frictions arising in part from its specificity (e.g., Belo et al., 2022; Bhandari et al., 2025; Chiavari and Goraya, 2025; Cloyne et al., 2022; Crouzet and Eberly, 2023; Peters and Taylor, 2017).

**Rising required return premia.** Gormsen and Huber (2023) document a systematic increase in firm-level hurdle rate wedges among publicly traded firms, defined as the difference between the rates of return managers require for investment approval and their perceived cost of capital. An increase in these wedges reflects a tightening in firms' internal investment criteria and therefore a more conservative investment response to expansion opportunities.

**Table 1:** Hurdle Rate and Capital Wedges

| *Dependent variable* | **Capital wedge** | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| *Hurdle rate wedge* | 3.01*** | 1.74*** | 2.65*** | 1.73*** |
| | (0.48) | (0.43) | (0.22) | (0.39) |
| *Fixed effects* | | | | |
| Firm | | | ✓ | ✓ |
| Sector | ✓ | ✓ | | |
| Time | ✓ | ✓ | ✓ | ✓ |
| *Capital weights* | | ✓ | | ✓ |
| Observations | 41,743 | 41,743 | 41,276 | 41,276 |

*Note.* The table reports regressions of firm-level capital wedges on the hurdle rate wedge constructed following Gormsen and Huber (2023), defined as the difference between firms' required hurdle rates and their perceived cost of capital. Columns (1) and (2) include sector and year fixed effects, while columns (3) and (4) include firm and year fixed effects. Columns (3) and (4) weight observations by firm capital stocks. Standard errors clustered at the firm level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 1 shows that the hurdle rate wedge measured by Gormsen and Huber (2023) is strongly positively associated with the capital wedge estimated in this paper, even after controlling for a rich set of fixed effects. Given the rise of 1.61 percentage points in the capital-weighted average hurdle rate wedge over time (as reported in Panel (a) of Figure C.6 in Appendix C.4) and a coefficient of 1.73 with our measure of capital wedges, representing our most conservative estimate, a simple back-of-the-envelope calculation suggests that changes in firms' required return premia may have increased capital wedges by as much as 2.78 percentage points—accounting for roughly 40 percent of the total rise.[22]

To further corroborate this mechanism, Appendix C.4 shows that hurdle rate wedges rise persistently around capital wedge quasi-shocks. The EOG case study discussed in the previous section provides a concrete illustration of how tighter internal investment thresholds can slow capital accumulation even in the presence of rapidly expanding sales. Taken together, these results suggest that rising hurdle rate wedges can therefore account for a non-negligible share of the increase in capital wedges documented in this paper.

# 6 Aggregate Implications

This section presents additional aggregate implications of the model. In particular, we show that the model implies a substantial decline in the true return on capital, a drag on aggregate productivity, and a rise in firm valuations. We also show that the framework is consistent with a broad set of additional macroeconomic trends documented in the recent literature.

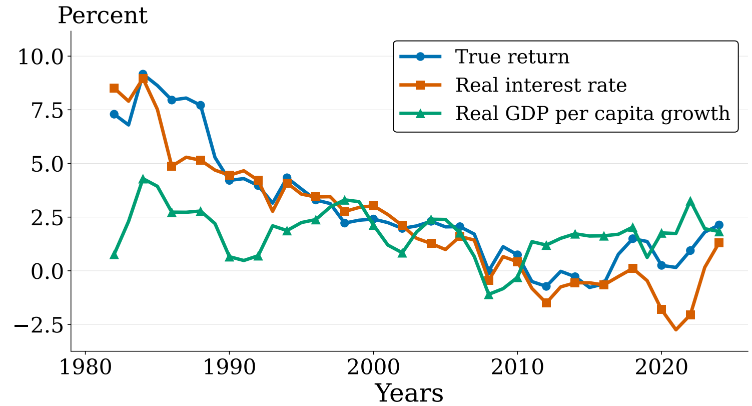
## 6.1 True Return on Capital

Figure 8 shows the evolution of the aggregate true return on capital, defined in Proposition 1 as the sum of the risk-free rate and the risk premium. The decline in the true return on capital reflects the fact that estimated risk premia remain relatively small and broadly stable over time, implying that the true return largely tracks the secular decline in the risk-free rate.

This decline carries important implications. Since the 2010s, the estimated true return on capital has remained mostly below the growth rate of GDP per capita. While this apparently contrasts with the high capital returns emphasized by Piketty (2014), it does not necessarily imply weaker wealth accumulation. Such incentives instead depend on the market value of claims on firms' future cash flows, which has continued to rise despite the decline in the true return to reproducible capital, a point to which we return below.

[22]Note that this estimate is likely a lower bound on the explanatory power of hurdle-rate wedges, as data are only available from the early 2000s onward. Our decomposition therefore captures only their contribution over the observed period. To the extent that hurdle-rate wedges had already begun rising before 2000, their contribution over the full sample would be larger.

**Figure 8:** True Return on Capital: 1982-2024

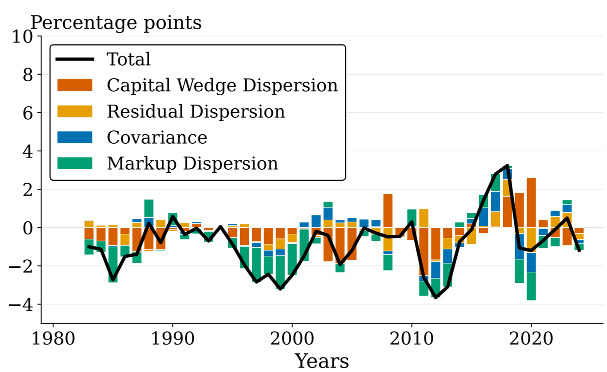



*Note.* Figure 8 illustrates the evolution of the true return on capital, the risk-free rate, and the three-year moving average of GDP per-capita growth.

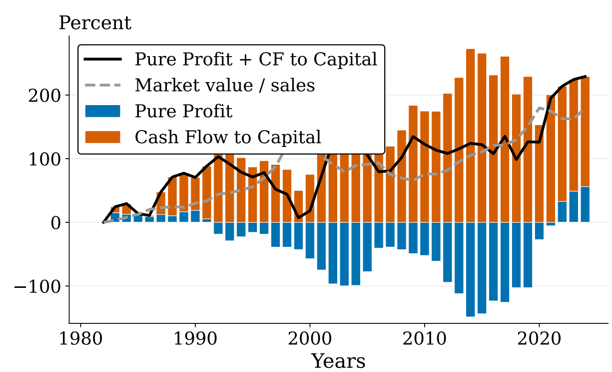
In addition, the fact that the true return on capital tracks the risk-free rate suggests that the tension between safe rates and returns on capital may be smaller than implied by conventional measures of capital returns, thereby supporting common practice to organize monetary policy around a single interest-rate framework.

## 6.2 Productivity Growth, Valuations, and Other Macroeconomic Trends

**Figure 9:** TFP Growth Contribution and Market Valuations




**(a)** TFP growth and allocative efficiency




**(b)** Stock market valuations

*Notes.* Panel (a) plots the centered 3-year moving average of productivity losses due to declining allocative efficiency, as measured by Equation (30), together with its individual components. Panel (b) plots the centered 3-year moving average of the market-value-to-sales ratio in Compustat and in the model, along with the model decomposition into cash flows accruing to pure profits and to capital.

This section investigates a range of additional predictions of the model, focusing in particular on its implications for productivity growth, stock market valuations, and other secular trends that have received substantial attention in the literature, and finds the model to be broadly consistent with the data.

**Productivity growth.** To study the productivity implications of the findings from the previous section, we follow David and Venkateswaran (2019) and specialize the model to a CES demand system, where $\sigma$ denotes the elasticity of substitution across goods. We accommodate the heterogeneous markup estimates from the previous section through firm-level output wedges layered on top of the common CES markup, and assume that markups and the revenue-based average product of capital, defined below, are jointly log-normally distributed.

Under these additional assumptions, changes in aggregate allocative efficiency, $AE$, arising from changes in the excess dispersion of firms' user cost of capital and markups can be expressed as follows:

$$\begin{aligned}\Delta AE_t \approx & -\underbrace{\tilde{\mathcal{E}}_{\mu}\Delta\mathbb{V}(\log(\mu_{jt}^{-1}))}_{\text{Markup dispersion}} + \underbrace{\tilde{\mathcal{E}}_{\mu,k}\Delta Cov(\log(ARPK_{jt}), \log(\mu_{jt}^{-1}))}_{\text{ARPK and markup covariance}} \\ & - \underbrace{\tilde{\mathcal{E}}_{k}\Delta\mathbb{V}(\log(\boldsymbol{\nabla}_{jt}))}_{\text{Wedge dispersion}} - \underbrace{\tilde{\mathcal{E}}_{k}\left(\Delta\mathbb{V}(\log(ARPK_{jt})) - \Delta\mathbb{V}(\log(\boldsymbol{\nabla}_{jt}))\right)}_{\text{Residual capital dispersion}},\end{aligned} \tag{30}$$

where $ARPK \equiv (p_{jt}q_{jt}) / (Q_{t-1}k_{jt})$ is the revenue-based average product of capital and $\tilde{\mathcal{E}}_{\mu} \equiv \frac{\mathcal{E}_k(1-(\frac{\sigma-1}{\sigma})\mathcal{E}_{\ell})}{2(1-(\frac{\sigma-1}{\sigma})(\mathcal{E}_k+\mathcal{E}_{\ell}))}$, $\tilde{\mathcal{E}}_{\mu,k} \equiv \frac{2(\frac{\sigma-1}{\sigma})\mathcal{E}_k\mathcal{E}_{\ell}}{2(1-(\frac{\sigma-1}{\sigma})(\mathcal{E}_k+\mathcal{E}_{\ell}))}$, and $\tilde{\mathcal{E}}_{k} \equiv \frac{(\mathcal{E}_k(1-(\frac{\sigma-1}{\sigma})\mathcal{E}_{\ell}))}{2(1-(\frac{\sigma-1}{\sigma})(\mathcal{E}_k+\mathcal{E}_{\ell}))}$.

The first term captures the effect of markup dispersion on allocative efficiency. The second term captures the extent to which the covariance between $ARPK$ and markups amplifies or mitigates these distortions. The final two terms capture the role of frictions in the user cost in generating dispersion in $ARPK$ and thereby reducing allocative efficiency, with the first isolating the direct contribution of capital wedges, while the second captures the contribution of the remaining components of the user cost.

Overall, we find that the model predicts a drag on productivity growth of approximately 0.84 percentage points over the sample period, with most of the slowdown concentrated in the pre-COVID period. Markup dispersion accounts for 55 percent of the decline in allocative efficiency, while dispersion in capital wedges emerges as the second most important force, accounting for 43 percent, see Table C.3. By contrast, residual dispersion beyond capital wedges plays only a minor role, while the covariance between markups and user costs contributes positively to productivity growth over the period. We also compute the drag on productivity growth for different values of the elasticity of substitution and the results seem to be robust to alternative values, see Figures C.7a and C.7b.

**Valuations.** The model is also consistent with the sharp rise in firms' stock market valuations despite weak tangible investment, as emphasized, among others, by Gutiérrez and Philippon (2017), Crouzet and Eberly (2023), and Atkeson et al. (2025).

To see this, we apply a Gordon-type valuation formula to aggregate free cash flows, yielding

$$\frac{V_t}{Y_t} \approx \left(\frac{1+g}{r-g}\right)\left(\frac{FCF_t}{Y_t}\right) = \left(\frac{1+g}{r-g}\right)\left(\frac{FCF_t^{\pi} + FCF_t^{k}}{Y_t}\right), \tag{31}$$

liwhere $Y_t$ denotes total sales; $FCF_t \equiv \sum_j d_{jt}$ denotes aggregate free cash flows, with firm-level free cash flows $d_{jt}$ defined by Equation (4); $FCF_t^{\pi} \equiv \sum_j (\Pi_{jt} - uc_{jt}^{k} k_{jt})$ the component of free cash flows arising from pure profits; and $FCF^k \equiv FCF_t - FCF^{\pi}$ denotes free cash flow accruing from capital.

Setting $\frac{1+g}{r-g}$ equal to 35.51—the average ratio of stock market valuations to free cash flows in the sample—generates a long-run pattern in valuations consistent with that observed in the data, as shown in Panel (b) of Figure 9, thus suggesting a central role for rising cash flows in driving rising stock market valuation (e.g., Atkeson et al., 2025).[23] In the model, the rise in valuations over the sample period is driven on average by the increase in free cash flows accruing from capital, i.e., adjusted revenue-based marginal returns net of investment expenditures and tax liabilities, while free cash flows arising from pure profits account for most of the increase after 2010.

**Other macroeconomic trends.** Because of the accounting nature of the framework, the model is also consistent with several macroeconomic trends beyond declining productivity growth and rising stock market valuations. In particular, it is consistent by construction with a broad set of empirical patterns documented in the recent literature, including the rise in concentration (Grullon et al., 2019), the decline in tangible investment (Gutiérrez and Philippon, 2017), the rise in intangible investment (Chiavari and Goraya, 2025), the evolution of the variable-cost share of sales and the rise in markups (De Loecker et al., 2020), and changing patterns of firm dynamism in Compustat (Gao et al., 2013).

[23] This calibration approach follows the strategy in Atkeson et al. (2026) and is equivalent to discounting a perpetuity at a rate of 0.028. While these values are plausible, they should be interpreted as illustrative, with the objective being to show that the model generates aggregate free cash flows broadly consistent with observed trends in stock market valuations.

# 7 Conclusion

This paper develops a dynamic general equilibrium framework for disaggregated economies that yields a closed-form decomposition of the return on capital into firm-level contributions from markups, corporate taxes, capital gains, risk premia, capital wedges, and distributional dynamics. Investigating why the measured return on capital has not declined in line with the risk-free rate, we uncover a dominant role for rising capital wedges across the distribution of firms. We find rising frictions associated with intangible capital and increasing discount rate wedges to be two promising candidate explanations for this phenomenon.

Our findings also have broader macroeconomic implications. First, we show that the true return on capital, as opposed to the measured return, has declined in line with the risk-free rate. Second, the model suggests that rising capital frictions have contributed to the slowdown in productivity growth and the rise in stock market valuations observed in the data.

This paper raises several challenging, albeit important, questions for future research. First, our framework treats markups, corporate taxation, capital gains, risk premia, and capital wedges as distinct primitives. In practice, however, these forces are likely to be jointly determined. Future research seeking to explain the divergence between the return on capital and the risk-free rate within a framework jointly determining them should be guided by—and remain consistent with—the empirical patterns documented here. Finally, although we apply our framework to the divergence between the return on capital and the risk-free rate in the United States, a natural extension is to study how the forces present in our framework contribute to cross-country differences in capital returns.

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# Online Appendix for:

# "The Return on Capital in Disaggregated Economies: Theory and Measurement"

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# A Model Appendix

## A.1 Proof of Lemma 1

As presented in Section 3.2, each firm chooses its variable input $\ell_{jt}$, next-period capital $k_{jt+1}$, and next-period bond holdings $b_{jt+1}$ to maximize the discounted value of after-tax dividends: (6) subject to (2)-(5). This is equivalent to solving for the following Lagrangian:

$$\mathcal{L}_j = \mathbb{E}_0 \sum_{t=0}^{\infty} \left( \prod_{s=0}^{t-1} M_{s+1} \right) \left\{ d_{jt} + \nabla_{jt+1} \left[ \kappa_{jt} - \frac{(1-\tau_t^c \delta_{x,jt}) Q_t k_{jt+1}}{1+r_t} \right] \right\}, \tag{A.1}$$

that can be written as

$$\begin{aligned}
\mathcal{L}_j = \mathbb{E}_0 \sum_{t=0}^{\infty} \left( \prod_{s=0}^{t-1} M_{s+1} \right) \Bigg\{ & p_{jt} z_{jt} \ell_{jt}^{\mathcal{E}_\ell} k_{jt}^{\mathcal{E}_k} - W_t \ell_{jt} - \phi_{jt} - Q_t \left( k_{jt+1} - (1-\delta_{jt}) k_{jt} \right) \\
& - \tau_t^c (p_{jt} z_{jt} \ell_{jt}^{\mathcal{E}_\ell} k_{jt}^{\mathcal{E}_k} - W_t \ell_{jt} - \phi_{jt} - \delta_{k,jt} Q_{t-1} k_{jt} \\
& - \delta_{x,jt} Q_t \left( k_{jt+1} - (1-\delta_{jt}) k_{jt} \right)) \\
& - b_{jt} + \frac{b_{jt+1}}{1+r_t} + \nabla_{jt+1} \left[ \kappa_{jt} - \frac{(1-\tau_t^c \delta_{x,jt}) Q_t k_{jt+1}}{1+r_t} \right] \Bigg\}.
\end{aligned}$$

The first order condition with respect to $k_{jt+1}$ is

$$\begin{aligned}
&(1-\tau_t^c \delta_{x,jt}) Q_t \left( 1 + \frac{\nabla_{jt+1}}{1+r_t} \right) = \\
&\quad \mathbb{E}_t M_{t+1} \left[ (1-\tau_{t+1}^c) \frac{\partial p_{jt+1} z_{jt+1} \ell_{jt+1}^{\mathcal{E}_\ell} k_{jt+1}^{\mathcal{E}_k}}{\partial k_{jt+1}} + (1-\delta_{jt+1})(1-\tau_{t+1}^c \delta_{x,jt+1}) Q_{t+1} + \tau_{t+1}^c \delta_{k,jt+1} Q_t \right],
\end{aligned} \tag{A.2}$$

where

$$\frac{\partial p_{jt+1} z_{jt+1} \ell_{jt+1}^{\mathcal{E}_\ell} k_{jt+1}^{\mathcal{E}_k}}{\partial k_{jt+1}} = \mathcal{E}_k p_{jt+1} z_{jt+1} \ell_{jt+1}^{\mathcal{E}_\ell} k_{jt+1}^{\mathcal{E}_k - 1} + \left( \frac{\partial p_{jt+1}}{\partial q_{jt+1}} \frac{q_{jt+1}}{p_{jt+1}} \right) \left( \frac{\partial q_{jt+1}}{\partial k_{jt+1}} \frac{k_{jt+1}}{q_{jt+1}} \right) \frac{p_{jt+1} q_{jt+1}}{k_{jt+1}}, \tag{A.3}$$

$$= \frac{MRPK_{jt+1}}{\mu_{jt+1}}. \tag{A.4}$$

The first order condition with respect to $b_{t+1}$ is

$$\frac{1}{1+r_t} = \mathbb{E}_t M_{t+1}. \tag{A.5}$$

Combining the two equilibrium conditions and rearranging yields

$$\left(1 + \frac{\nabla_{jt+1}}{1+r_t}\right) = \\ \mathbb{E}_t M_{t+1}\left[\frac{(1-\tau^c_{t+1})MRPK_{jt+1}}{\mu_{jt+1}(1-\tau^c_t\delta_{x,jt})Q_t} + \frac{(1-\delta_{jt+1})(1-\tau^c_{t+1}\delta_{x,jt+1})Q_{t+1}}{(1-\tau^c_t\delta_{x,jt})Q_t} + \frac{\tau^c_{t+1}\delta_{k,jt+1}}{(1-\tau^c_t\delta_{x,jt})}\right]. \tag{A.6}$$

The right-hand side is the conditional expectation of a product, which decomposes into the product of conditional expectations plus the conditional covariance:

$$\left(1 + \frac{\nabla_{jt+1}}{1+r_t}\right) = \mathbb{E}_t\left[M_{t+1}\right]\mathbb{E}_t\left[\frac{(1-\tau^c_{t+1})MRPK_{jt+1}}{\mu_{jt+1}(1-\tau^c_t\delta_{x,jt})Q_t} + \frac{(1-\delta_{jt+1})(1-\tau^c_{t+1}\delta_{x,jt+1})Q_{t+1}}{(1-\tau^c_t\delta_{x,jt})Q_t} + \frac{\tau^c_{t+1}\delta_{k,jt+1}}{(1-\tau^c_t\delta_{x,jt})}\right] \\ + \mathbb{C}ov_t\left(M_{t+1}, \frac{(1-\tau^c_{t+1})MRPK_{jt+1}}{\mu_{jt+1}(1-\tau^c_t\delta_{x,jt})Q_t} + \frac{(1-\delta_{jt+1})(1-\tau^c_{t+1}\delta_{x,jt+1})Q_{t+1}}{(1-\tau^c_t\delta_{x,jt})Q_t} + \frac{\tau^c_{t+1}\delta_{k,jt+1}}{(1-\tau^c_t\delta_{x,jt})}\right). \tag{A.7}$$

Substituting the bond Euler equation, $\mathbb{E}_t[M_{t+1}] = (1+r_t)^{-1}$, and multiplying both sides by $(1+r_t)$, the covariance term is multiplied by $(1+r_t) = 1/\mathbb{E}_t[M_{t+1}]$; multiplying and dividing it by $\mathbb{V}ar_t[M_{t+1}]$ expresses it as $-\boldsymbol{\beta}_{jt+1}\boldsymbol{\lambda}_{t+1} = -\boldsymbol{\zeta}_{jt+1}$, the negative of the risk premium of Lemma 1.

Next, define the expectational error $\varepsilon_{jt+1}$ as the realized value of the term in brackets minus its conditional expectation, so that $\mathbb{E}_t[\varepsilon_{jt+1}] = 0$ by construction. Replacing the conditional expectation with its realized value minus $\varepsilon_{jt+1}$ and absorbing the error into the augmented wedge $\boldsymbol{\nabla}_{jt+1} \equiv \nabla_{jt+1} + \varepsilon_{jt+1}$ of Lemma 1, we obtain the ex post identity

$$
\begin{aligned}
&1 + r_t + \boldsymbol{\nabla}_{jt+1} = \\
&\frac{(1-\tau^c_{t+1})MRPK_{jt+1}}{\mu_{jt+1}(1-\tau^c_t\delta_{x,jt})Q_t} + (1-\delta_{jt+1}) \\
&+ \left(\frac{(1-\delta_{jt+1})(1-\tau^c_{t+1}\delta_{x,jt+1})Q_{t+1}}{(1-\tau^c_t\delta_{x,jt})Q_t} - (1-\delta_{jt+1})\right) + \frac{\tau^c_{t+1}\delta_{k,jt+1}}{(1-\tau^c_t\delta_{x,jt})} \\
&- \frac{\mathbb{C}ov_t\left(M_{t+1}, \frac{(1-\tau^c_{t+1})MRPK_{jt+1}}{\mu_{jt+1}(1-\tau^c_t\delta_{x,jt})Q_t} + \frac{(1-\delta_{jt+1})(1-\tau^c_{t+1}\delta_{x,jt+1})Q_{t+1}}{(1-\tau^c_t\delta_{x,jt})Q_t} + \frac{\tau^c_{t+1}\delta_{k,jt+1}}{(1-\tau^c_t\delta_{x,jt})}\right)}{\mathbb{V}ar_t[M_{t+1}]}\left(-\frac{\mathbb{V}ar_t[M_{t+1}]}{\mathbb{E}_t[M_{t+1}]}\right),
\end{aligned}
\tag{A.8}
$$

where the second and third lines add and subtract $(1-\delta_{jt+1})$ to isolate the capital-gains component. Rearranged and lagged by one period, this yields exactly Equation (12). This completes the proof. ■

## A.2 Proof of Proposition 1

To prove Proposition 1, we start from the definition of measured firm-level return on capital in Equation (13) and use the equilibrium condition for and capital in Equation (12) as follows:

$$
R_{jt} \equiv \frac{p_{jt}q_{jt} - \phi_{jt} - \delta_{jt}Q_{t-1}k_{jt} - W_t\ell_{jt}}{Q_{t-1}k_{jt}}, \tag{A.9}
$$

$$
= \frac{p_{jt}q_{jt} - \phi_{jt} - \left(\frac{1-\tau^c_t}{(1-\tau^c_{t-1}\delta_{x,jt-1})\mu_{jt}}\frac{MRPK_{jt}}{Q_{t-1}} - r_{t-1} - \boldsymbol{\varrho}_{jt} - \boldsymbol{\tau}_{jt} - \boldsymbol{\nabla}_{jt} - \boldsymbol{\zeta}_{jt}\right)Q_{t-1}k_{jt} - W_t\ell_{jt}}{Q_{t-1}k_{jt}}, \tag{A.10}
$$

$$
= \frac{p_{jt}q_{jt} - \phi_{jt} - \left(\frac{1-\tau^c_t}{(1-\tau^c_{t-1}\delta_{x,jt-1})\mu_{jt}}\frac{MRPK_{jt}}{Q_{t-1}}\right)Q_{t-1}k_{jt} - W_t\ell_{jt}}{Q_{t-1}k_{jt}} + r_{t-1} + \boldsymbol{\varrho}_{jt} + \boldsymbol{\tau}_{jt} + \boldsymbol{\nabla}_{jt} + \boldsymbol{\zeta}_{jt}, \tag{A.11}
$$

$$
= \frac{p_{jt}q_{jt} - \phi_{jt} - uc^k_{jt}Q_{t-1}k_{jt} - W_t\ell_{jt}}{Q_{t-1}k_{jt}} + r_{t-1} + \boldsymbol{\varrho}_{jt} + \boldsymbol{\tau}_{jt} + \boldsymbol{\nabla}_{jt} + \boldsymbol{\zeta}_{jt}, \tag{A.12}
$$

$$
= \boldsymbol{\pi}_{jt} + r_{t-1} + \boldsymbol{\varrho}_{jt} + \boldsymbol{\tau}_{jt} + \boldsymbol{\nabla}_{jt} + \boldsymbol{\zeta}_{jt}; \tag{A.13}
$$

which proves the first part of the proposition.

To prove the second part of the proposition, we start with the definition of pure profits per unit of capital applied above and use the fact that in equilibrium $\frac{1-\tau_t^c}{(1-\tau_{t-1}^c\delta_{x,jt-1})\mu_{jt}}\frac{MRPK_{jt}}{Q_{t-1}} = uc_{jt}^k$ together with the equilibrium condition for the variable input in Equation (7) as follows:

$$\pi_{jt} = \frac{p_{jt}q_{jt} - \phi_{jt} - uc_{jt}^k Q_{t-1}k_{jt} - W_t\ell_{jt}}{Q_{t-1}k_{jt}}, \tag{A.14}$$

$$= \frac{p_{jt}q_{jt} - \phi_{jt} - \frac{1-\tau_t^c}{(1-\tau_{t-1}^c\delta_{x,jt-1})\mu_{jt}}\frac{MRPK_{jt}}{Q_{t-1}}Q_{t-1}k_{jt} - \frac{MRPL_{jt}}{\mu_{jt}}\ell_{jt}}{Q_{t-1}k_{jt}}, \tag{A.15}$$

$$= \frac{p_{jt}q_{jt} - \phi_{jt} - \frac{1-\tau_t^c}{1-\tau_{t-1}^c\delta_{x,jt-1}}\mathcal{E}_k\frac{p_{jt}q_{jt}}{\mu_{jt}} - \mathcal{E}_\ell\frac{p_{jt}q_{jt}}{\mu_{jt}}}{Q_{t-1}k_{jt}}; \tag{A.16}$$

which, after collecting and rearranging terms, yields the ratio of pure profits per unit of installed capital in the second part of the proposition. This completes the proof. ■

# B Data Appendix

This appendix provides a detailed description of the data sources, sample construction, and variable definitions used in the empirical analysis.

## B.1 Data Sources

**Firm-level financial data.** The primary firm-level data source is the Compustat North America Annual Fundamentals database, accessed through Wharton Research Data Services. Compustat provides standardized balance-sheet and income-statement information for publicly traded U.S. firms, including sales (`sale`), cost of goods sold (`cogs`), selling, general, and administrative expenses (`xsga`), gross and net property, plant, and equipment (`ppegt`, `ppent`), research and development expenditures (`xrd`), intangible assets (`intan`), goodwill (`gdwl`), depreciation and amortization (`dp`), employment (`emp`), and NAICS industry classifications.

**Stock market data.** Monthly stock returns are obtained from the Monthly Stock File of the Center for Research in Security Prices. We restrict the sample to common stocks (share codes 10 and 11) listed on the NYSE, AMEX, or NASDAQ (exchange codes 1, 2, and 3). Firm-level stock returns are linked to Compustat using the CRSP–Compustat Merged linking table.

**Risk factor data.** Our baseline asset-pricing specification uses the five-factor model of Hou et al. (2015), which includes the market ($r^{\text{MKT}}$), size ($r^{\text{ME}}$), investment ($r^{\text{IA}}$), profitability ($r^{\text{ROE}}$), and expected-growth ($r^{\text{EG}}$) factors. These data are obtained from global-q.org. In robustness exercises, we additionally use the Fama–French three- and five-factor models (Fama and French, 2023), obtained from Kenneth French's data library.

**National accounts.** Aggregate quantities, prices, and capital stocks are obtained from the Bureau of Economic Analysis (BEA) National Income and Product Accounts (NIPA) and Fixed Asset Tables (FAT). Gross domestic product and investment components (nonresidential structures, equipment, and intellectual property products) are obtained from NIPA Table 1.1.5. Implicit price deflators for GDP and investment components are from NIPA Table 1.1.9. Gross value added by sector, including net operating surplus and proprietors' income, is from NIPA Table 1.10. National income by type of income, including corporate profits with inventory valuation and capital consumption adjustments, is from NIPA Table 1.12. Gross value added of domestic corporate business, including taxes on production and corporate income, is from NIPA Table 1.14. Federal government current tax receipts are from NIPA Table 3.2. Net value added of the housing sector is from NIPA Table 7.4.5. Current-cost net stocks of private fixed assets by asset type are from FAT Table 2.1. Current-cost net stocks of private nonresidential fixed assets by industry and legal form are from FAT Table 4.1.

**Interest rates and inflation.** Interest-rate and inflation data are obtained from the Federal Reserve Economic Data database. These include the market yield on U.S. Treasury securities at 10-year constant maturity (DGS10), one-year-ahead inflation expectations from the University of Michigan Survey (MICH), consumer price inflation (FPCPITOTLZGUSA), the effective federal funds rate (FEDFUNDS), and Moody's seasoned AAA and BAA corporate bond yields.

**Corporate tax data.** Statutory corporate income tax rates are obtained from historical IRS publications covering the period 1929-2023. Effective tax rates on capital income are taken from Gravelle (2006). The investment-deductibility parameters used in the analysis are constructed from the statutory provisions governing depreciation allowances and investment expensing.

**Hurdle rate data.** Firm-level estimates of perceived costs of capital and hurdle rates are obtained from Version 3.0 of the dataset developed by Gormsen and Huber (2023). The dataset provides annual measures of firms' perceived costs of capital and hurdle rates for the period 2002-2021.

## B.2 Aggregate Return on Capital and Risk-Free Rate

**Measured return on capital in national accounts.** We construct the measured return on capital in the national accounts following Gomme et al. (2011) and Reis (2022):

$$R_t = \frac{\text{NOS}_t - \text{NOS}_t^{\text{housing}} - \frac{2}{3}(\Pi_t - \Pi_t^{\text{housing}})}{\text{Private non-residential capital stock}_t} \times 100, \tag{B.1}$$

where $\text{NOS}_t$ denotes net operating surplus (NIPA Table 1.10, Line 9), $\Pi_t$ denotes proprietors' income (NIPA Table 1.10, Line 13), housing-sector components are obtained from NIPA Table 7.4.5, and the private non-residential capital stock is obtained from the Fixed Asset Tables and includes equipment, structures, intellectual property products, and inventories, excluding residential assets. Following the literature, we attribute two-thirds of non-housing proprietors' income to labor compensation and one-third to capital income, while housing proprietors' income is excluded in full.

**Risk-free rate.** The real risk-free rate is constructed as the difference between the nominal yield on 10-year U.S. Treasury securities and expected inflation:

$$r_t = \texttt{DGS10}_t - \mathbb{E}_t[\pi_{t+1}], \tag{B.2}$$

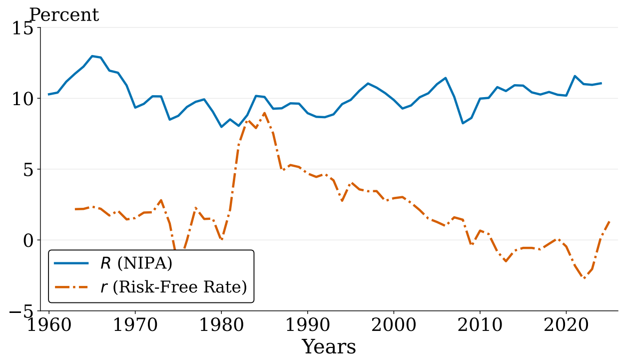
where $\mathbb{E}_t[\pi_{t+1}]$ denotes expected inflation measured using the University of Michigan Survey of Consumers one-year-ahead median inflation forecast. For years in which these survey data are unavailable, expected inflation is imputed using forecasts from a first-order autoregressive model of realized CPI inflation.

**Historical evolution of the measured return on capital and risk-free rate.** Figure B.1 extends the comparison of the NIPA-based return on capital and the real risk-free rate back to 1960.

## B.3 Relative Capital Prices

Here we compare the relative price of investment constructed from the national accounts with the baseline measure used in the main text, which is based on the Törnqvist chain-weighted investment deflator proposed by Gourio et al. (2022).

**Figure B.1:** Aggregate Return on Capital and the Risk-Free Rate, 1960–2024



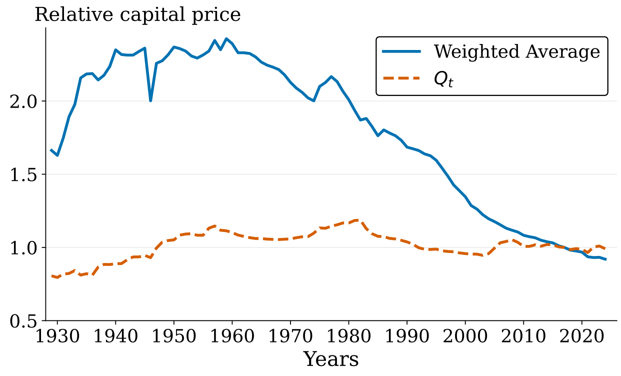

*Note.* The solid blue line plots the historical evolution of the measured return on capital in the national accounts, while the dash-dotted red line plots the real risk-free rate. Both series are expressed in percent and cover the period 1960–2024.

To construct the national-accounts investment deflator, let $I_t^a$ denote nominal gross fixed investment in asset class $a$, where $a \in$ equipment, structures, IPP, obtained from NIPA Table 1.1.5. Define the current-period nominal investment share as $\omega_t^a = I_t^a / \sum_{a'} I_t^{a'}$, and let $P_t^a$ denote the price deflator for asset class $a$. The aggregate investment deflator and its relative-price counterpart are given by

$$P_t^K = \sum_a \omega_t^a P_t^a, \qquad \text{and} \qquad Q_t = \frac{P_t^K}{P_t^{GDP}}; \tag{B.3}$$

where $Q_t$ is normalized to unity in 2017.

**Figure B.2:** Alternative Measures of the Relative Price of Investment, 1929–2024




*Note.* The dashed red line plots the relative price of investment based on the Törnqvist chain-weighted aggregate capital price index proposed by Gourio et al. (2022). The solid blue line plots the national-accounts relative price of investment based on an investment-weighted average of the price deflator of each asset category. Data are shown from 1929 to 2024.

Figure B.2 compares the Törnqvist-based relative price used in the main text with its national-accounts counterpart. The two series differ throughout the sample because the Törnqvist measure uses capital-stock weights, whereas the national-accounts measure uses investment-flow weights, assigning different importance to individual asset classes, as emphasized by Gourio et al. (2022). For our purposes, however, the key object is not the relative price of investment itself but the contribution of the associated capital-gains term to the gap between the measured return on capital and the risk-free rate. Table C.1 shows that this contribution remains quantitatively small across alternative measures of the relative price of investment.

## B.4 Compustat Sample Construction

We construct the estimation sample from Compustat North America as follows. We begin with the universe of firm-year observations with non-missing fiscal-year and NAICS industry classifications. When a firm is assigned to multiple industries within a given year, we retain its primary industry classification. We then remove duplicate firm-year observations identified by `gvkey` and `fyear`.

We exclude firms in NAICS industries 11 (Agriculture, Forestry, Fishing, and Hunting), 22 (Utilities), 49 (Postal Service and Warehousing), 61 (Educational Services), and 81 (Other Services), as these sectors are either regulated, predominantly non-profit, or characterized by capital structures that differ substantially from those of the corporate sector. We further require strictly positive values for sales, cost of goods sold, physical capital, intangible capital, and selling, general, and administrative expenses.

Finally, to mitigate the influence of outliers, we winsorize sales, cost of goods sold, total capital, and SG&A expenses at the 0.5th and 99.5th percentiles of their annual distributions.

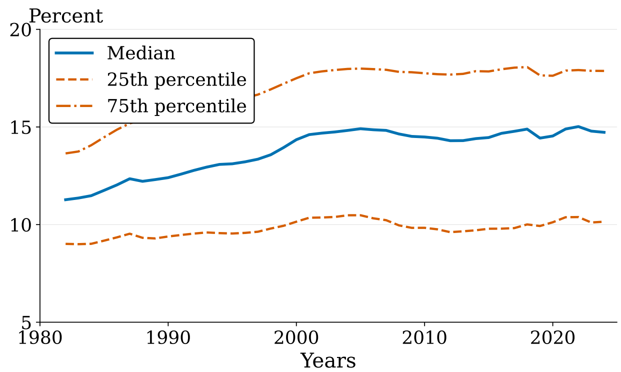
**Table B.1:** Summary Statistics, 1980–2024

| | N | Mean | SD | P10 | P25 | P50 | P75 | P90 |
|---|---|---|---|---|---|---|---|---|
| Sales | 178,141 | 2,108.7 | 6,365.7 | 8.7 | 40.1 | 235.2 | 1,196.3 | 4,839.1 |
| Cost of Goods Sold | 178,141 | 1,355.8 | 4,358.3 | 4.4 | 21.5 | 131.7 | 722.5 | 3,049.6 |
| SG&A Expenses | 178,141 | 240.5 | 762.1 | 2.2 | 6.4 | 27.7 | 132.8 | 518.3 |
| Physical Capital | 178,141 | 1,399.9 | 5,293.2 | 2.6 | 11.6 | 79.2 | 546.6 | 2,870.8 |
| Total Capital | 178,141 | 2,222.0 | 7,729.4 | 12.1 | 40.5 | 196.5 | 1,047.2 | 4,600.8 |
| Employees (thousands) | 166,782 | 7.8 | 23.9 | 0.0 | 0.2 | 1.0 | 4.8 | 18.0 |

*Note.* All monetary values are expressed in millions of 2017 dollars, and employment is measured in thousands of employees. The sample consists of Compustat firms observed between 1980 and 2024 after applying the sample restrictions described in this section.

Table B.1 reports summary statistics for the main firm-level variables used throughout the paper. The sample consists of Compustat firms observed between 1980 and 2024 after applying the sample restrictions described above.

**Figure B.3:** Distribution of Firm-Level Depreciation Rates, 1982-2024




*Note.* The figure plots the median, 25th percentile, and 75th percentile of firm-level economic depreciation rates over the period 1982-2024.

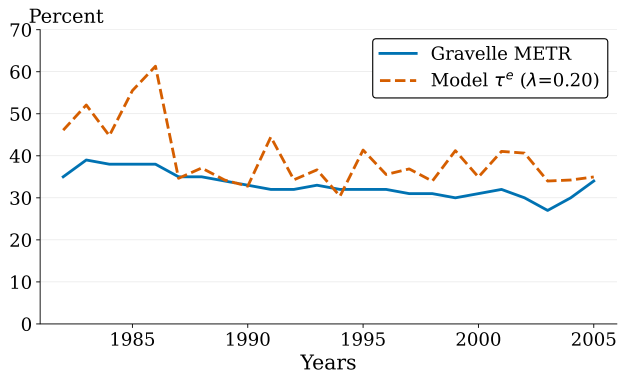
Figure B.3 presents the distribution of firm-level depreciation rates constructed as described in Section 4.1. Two patterns emerge. First, depreciation rates exhibit substantial cross-sectional dispersion, reflecting heterogeneity in firms' capital composition and, in particular, differences in the relative importance of tangible and intangible capital. Second, average depreciation rates have increased over time, consistent with the well-documented shift in firms' capital stocks from low-depreciation tangible assets toward higher-depreciation intangible assets.

## B.5 Corporate Taxation

**Corporate taxation validation.** Here we validate our choice of the investment deductibility parameter, $\delta_{x,t} = 0.20$, following Atkeson et al. (2025), against two independent moments. First, this value implies a close match between the share of aggregate corporate tax revenues accounted for by firms in our Compustat sample and independent estimates for publicly traded C corporations. Second, it aligns the model-implied effective corporate tax rate with the historical estimates reported by Gravelle (2006).

To assess the first moment, we aggregate model-implied corporate tax revenues across firms in our Compustat sample and compare them with the corresponding NIPA measure of federal corporate tax revenues. The Compustat aggregate accounts, on average, for 73.6% of total NIPA corporate tax revenues over the period 1982-2024. This figure is broadly consistent with the external benchmark reported by Dobridge et al. (2023, Table 1, Panel B), who use IRS administrative tax-return microdata and find that publicly traded C corporations paid 71.6% of total C-corporation taxes in 2016.

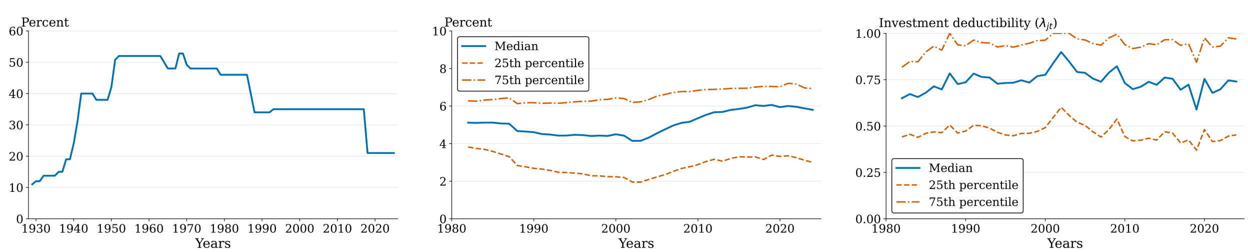
**Figure B.4:** Model-Implied and Gravelle (2006) Effective Corporate Tax Rates




*Note.* The solid blue line plots the effective corporate tax rate reported by Gravelle (2006). The dashed red line plots the corresponding model-implied effective corporate tax rate. Both series are expressed in percentage points and cover the period 1982-2005, corresponding to the years for which the Gravelle series is available.

To assess the second moment, Figure B.4 compares the effective corporate tax rate implied by the model with the historical series constructed by Gravelle (2006). The figure shows that the two series track one another throughout the sample, providing additional support for our measurement of investment deductibility and, more generally, for our treatment of corporate taxation.

**Figure B.5:** Statutory Corporate Tax Rates, Deductible Depreciation Rates, and Investment Deductibility Rates over Time




**(a)** Statutory tax **(b)** Deductible depreciation **(c)** Investment Deductibility

*Note.* Panel (a) shows the evolution of the statutory corporate tax rate. Panel (b) reports the evolution of the distribution of deductible depreciation rates. Panel (c) reports the evolution of the distribution of investment deductibility rates.

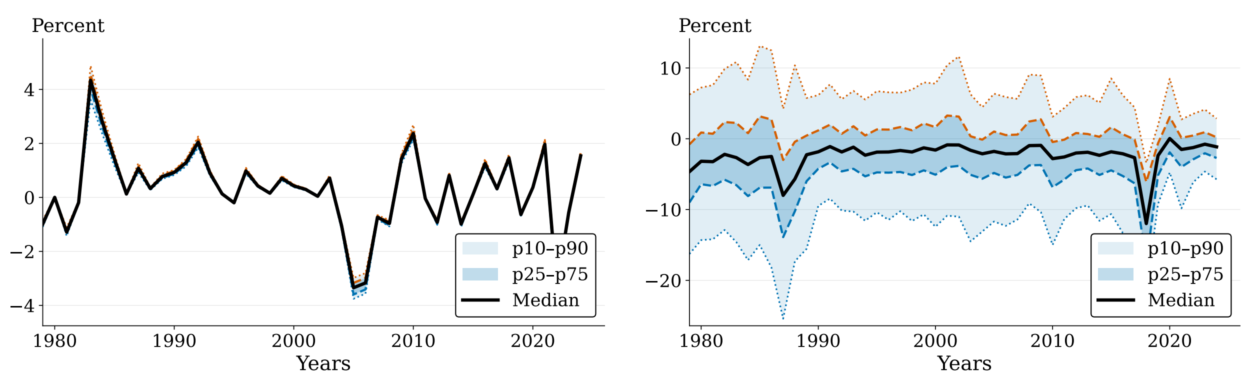
**Statutory corporate tax rates, depreciation deductibility, and investment deductibility.** Figure B.5 reports the evolution of the statutory corporate tax rate, $\tau_t^c$, together with the distributions of depreciation deductibility, $\delta_{k,jt}$, and investment deductibility, $\delta_{x,jt}$, measured as described in the main text.

Panel (a) shows the decline in statutory corporate tax rates since the 1980s. Panel (b) reports the evolution of deductible depreciation rates. These rates are lower than economic depreciation rates because a substantial fraction of depreciation associated with intangible capital is not deductible under current accounting and tax rules. At the same time, deductible depreciation rates have increased over time, reflecting the growing share of deductible intangible capital recorded on firms' balance sheets. Finally, Panel (c) reports the evolution of investment deductibility rates. These rates have remained broadly stable over time because changes in the composition of investment between tangible capital and balance-sheet intangible capital have largely offset one another, leaving the share of total deducible investment mostly unchanged over time.

## B.6 Cross-sectional Distribution of Capital Gains and Taxation

Section 4.2.1 reports the capital-weighted aggregate evolution of the capital-gains and taxation components of the return decomposition. Here we document the corresponding evolution of their full cross-sectional distributions. Figure B.6 plots, for each component, the median together with the interquartile range and the 10th-90th percentile range across firms in each year.

**Figure B.6:** Evolution of the Cross-sectional Distribution of Capital Gains and Taxation




**(a)** Capital gains **(b)** Taxation

*Note.* Each panel plots the cross-sectional 10th, 25th, 50th, 75th, and 90th percentiles of the firm-level component by year. Shaded bands indicate the interquartile range (25th–75th percentiles) and the 10th–90th percentile range. Panel (a) shows the capital-gains component, while Panel (b) shows the corporate-taxation component. Both series are expressed in percentage points.

Overall, we find that the distribution of capital gains is considerably less dispersed than that of the taxation component. Nevertheless, neither component exhibits a pronounced trend over time in any of the distributional moments considered, confirming the broad stability of both series documented in the main text.

## B.7 Production Function Estimation, Markups, and Profit Rates

### B.7.1 Production Function Estimation

We estimate the production function in Equation (2) at the 2-digit industry level using rolling ten-year windows centered on each year. Below we present the baseline approach together with several complementary approaches we employ to assess the robustness of our conclusions.

**System GMM with first stage (baseline).** Our baseline estimator combines a control-function first stage with a system GMM estimator. In the first stage, we regress log revenues on flexible functions of log inputs and the oligopoly instrument proposed by Ackerberg and De Loecker (2024), namely competitors' total revenues within the same 4-digit industry. In the second stage, we use the fitted values from the first stage within a system GMM framework (Blundell and Bond, 1998), which exploits both level and differenced moment conditions while accommodating firm-specific fixed effects.

**System GMM without first stage.** This specification bypasses the control-function first stage and applies the system GMM estimator directly to log revenues. By omitting the oligopoly instrument, it does not account for imperfect competition. At the same time, it avoids the scalar unobservability restriction underlying the control-function approach, whose limitations have recently been emphasized by Bond et al. (2021).

**ACF with oligopoly instruments.** Following Ackerberg et al. (2015), this specification implements the control-function approach using a two-step procedure. The first stage is identical to the baseline specification. In the second stage, rather than employing system GMM, we use the standard ACF moment conditions, which exploit the orthogonality between innovations to the productivity process and a set of instruments consisting of current capital and lagged variable inputs, as well as their lags.

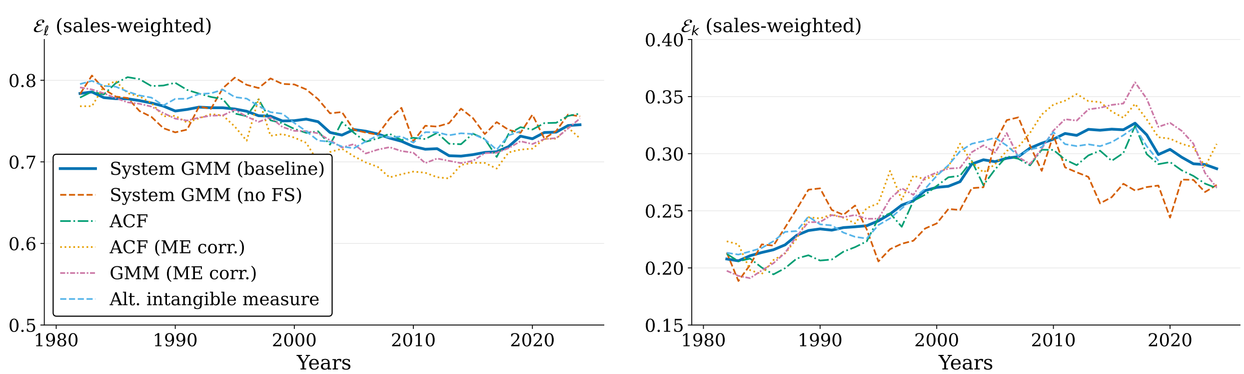
**ACF with measurement error correction.** This specification modifies the ACF estimator by instrumenting capital with investment in the first stage and replacing the capital stock with lagged investment in the second-stage moment conditions, following Collard-

Wexler and De Loecker (2015). As shown by Collard-Wexler and De Loecker (2015), this approach eliminates the bias arising from measurement error in capital.

**System GMM with measurement error correction.** This specification incorporates the same measurement-error correction within the system GMM framework of the baseline estimator. It therefore combines the ability of system GMM to accommodate firm fixed effects and control for permanent firm characteristics with an estimation procedure that is robust to capital mismeasurement.

**System GMM with alternative intangible capital measure.** This specification uses the baseline production function estimator but adopts an alternative measure of intangible capital. Specifically, for the components of intangible capital constructed using the perpetual inventory method, we replace the baseline assumption that firms begin with zero intangible capital in their first year of observation. Instead, we initialize these components at the ratio of average investment to the depreciation rate, which corresponds to the steady-state capital stock implied by a constant investment rate.

**Figure B.7:** Output Elasticities across Production Function Specifications




**(a)** Variable Input Elasticity $\mathcal{E}_\ell$

**(b)** Capital Elasticity $\mathcal{E}_k$

*Note.* This figure plots sales-weighted output elasticities of the variable input (Panel (a)) and capital (Panel (b)) across six alternative production-function specifications. All estimates are obtained at the 2-digit industry level using rolling ten-year estimation windows.

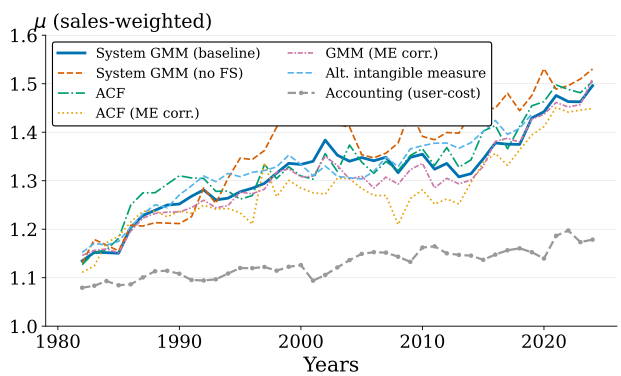
**Results.** Figures B.7 plot the sales-weighted output elasticities implied by the six production function specifications. Panel (a) shows the evolution of the variable-input elasticity, while Panel (b) shows the evolution of the capital elasticity. The variable-input elasticity, $\mathcal{E}_\ell$, declines modestly over the sample period, whereas the capital elasticity, $\mathcal{E}_k$, increases gradually. Despite differences in estimation methodology, the implied time-series patterns are broadly similar across specifications.

### B.7.2 Markups

Figure B.8 plots the time-series evolution of sales-weighted markups across all specifications. These include markups based on the ratio estimator of De Loecker and Warzynski (2012) using the alternative production-function estimates described above, as well as markups based on the production-function-free accounting approach of Baqaee and Farhi (2020). The latter measure defines markups as the ratio of sales to gross profits net of depreciation, where gross profits are measured as sales less the cost of goods sold, SG&A and depreciation.

Overall, all measures exhibit an upward trend over the sample period, consistent with the large literature documenting rising markups (e.g., Syverson, 2024). Markups based on the ratio estimator display a quantitatively similar and pronounced increase across specifications. The accounting-based measure implies a more modest rise, although it too exhibits a substantial upward trend. Taken together, these results suggest that the rise in markups is not driven by a particular production-function estimator or measurement methodology.

**Figure B.8:** Markups across Production Function Specifications




*Note.* This figure plots the sales-weighted aggregate markup implied by the ratio estimator of De Loecker and Warzynski (2012) across all alternative production-function estimators described in this appendix, together with the production-function-free accounting markup measure of Baqaee and Farhi (2020).

To further support this conclusion, Table B.2 reports the pairwise correlations among the seven markup measures (the six production-function-based estimates and the accounting measure). The six production-function specifications are highly correlated with one another, with correlations exceeding 0.95 for almost every pair, confirming that the choice of production-function estimator has little influence on the measured cross-sectional variation in markups. The accounting measure is also positively correlated with the production-function-based measures, with an average correlation of approximately 0.32, indicating that it captures a related dimension of markup variation despite relying on a fundamentally different measurement approach.

**Table B.2:** Correlation Matrix of Firm-Level Markup Measures

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| (1) *Sys. GMM (baseline)* | 1.000 | | | | | | |
| (2) *Sys. GMM (no FS)* | 0.956 | 1.000 | | | | | |
| (3) *ACF* | 0.993 | 0.949 | 1.000 | | | | |
| (4) *ACF (ME corr.)* | 0.989 | 0.949 | 0.995 | 1.000 | | | |
| (5) *Sys. GMM (ME corr.)* | 0.997 | 0.963 | 0.992 | 0.990 | 1.000 | | |
| (6) *Sys. GMM (Alt. intangibles)* | 0.998 | 0.957 | 0.992 | 0.989 | 0.996 | 1.000 | |
| (7) *Accounting measure* | 0.323 | 0.303 | 0.320 | 0.315 | 0.320 | 0.321 | 1.000 |

*Note.* This table reports the pairwise correlations among alternative firm-level markup measures. The measures include markups implied by the ratio estimator of De Loecker and Warzynski (2012) under each of the production-function estimators described in this appendix, as well as the production-function-free accounting markup measure of Baqaee and Farhi (2020).

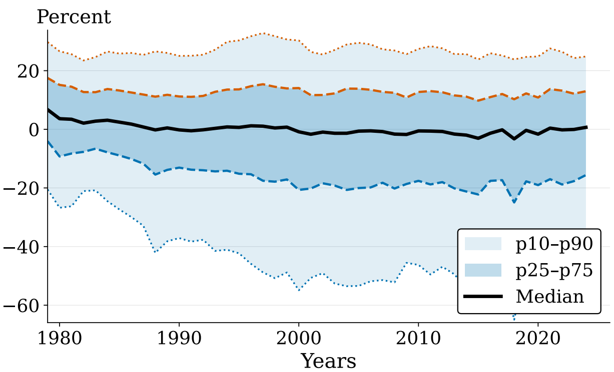
### B.7.3 Profit Rate Measures

**Cross-sectional distribution over time.** Figure B.9 reports the evolution of the cross-sectional distribution of firm-level profit rates, $\pi_{jt}$, over time. The figure plots the median together with the interquartile range and the 10th-90th percentile range across firms in each year.

Overall, we find that the distribution has become more dispersed over time, with a growing lower tail of firms exhibiting increasingly negative profit rates, while the median has remained broadly stable. This pattern indicates that the rise in capital-weighted profit rates documented in the main text reflects changes in the allocation of capital toward more profitable firms rather than a broad-based increase in profitability across the firm distribution, consistent with the literature on rising concentration and the growing importance of superstar firms. We next show why our estimated increase in profit rates is more modest than that reported in parts of the existing literature and trace this difference to the measurement of the user cost of capital.

**Comparison with the literature.** A natural question is why we estimate a more modest increase in profit rates than the existing literature (e.g., De Loecker et al., 2020), despite re-

**Figure B.9:** Evolution of the Cross-Sectional Distribution of Profit Rates




*Note.* The figure plots the 10th, 25th, 50th, 75th, and 90th percentiles of the cross-sectional distribution of the baseline firm-level profit wedge, $\pi_{jt}$, by year. Shaded bands denote the interquartile range (p25-p75) and the 10th-90th percentile range. The series is expressed in percent.

covering similar trends in production function elasticities and markups. Our measure of the aggregate profit rate differs from the standard approach along two dimensions. First, we aggregate firm-level profit rates using capital weights rather than sales weights. Second, we use the generalized user cost of capital from Lemma 1 instead of the conventional user cost proposed by Hall and Jorgenson (1967).

We begin by evaluating the first explanation, namely that the difference arises from the weighting scheme. To do so, we recompute the aggregate profit rate using sales weights rather than capital weights while leaving all other aspects of the measurement unchanged. Panel (a) of Figure B.10 reports the resulting series. The alternative measure closely tracks our baseline estimate, indicating that differences in weighting schemes account for little of the divergence between our results and those in the existing literature.

To explore the second candidate explanation, it is useful to start from the profit measure commonly used in the literature (e.g., De Loecker et al., 2020), defined as follows:

$$\Pi_{jt}^{\mathrm{DEU}} = p_{jt}q_{jt} - W_t\ell_{jt} - \phi_{jt} - \left(r_{t-1} + \delta_{jt} + \zeta_{jt}\right) Q_{t-1}k_{jt}, \tag{B.4}$$

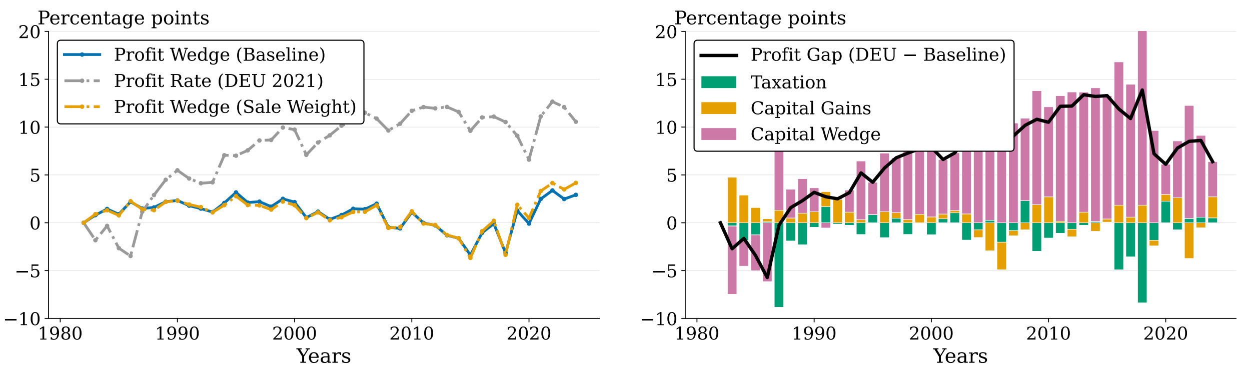
where all terms coincide with our baseline measure except for the user cost of capital, which is given by the conventional Hall and Jorgenson (1967) formulation, $r_{t-1} + \delta_{jt} + \zeta_{jt}$. Because this measure omits several components of the generalized user cost developed in this paper—namely capital gains, corporate taxation, and capital wedges—it implies a lower cost of capital and therefore attributes a larger share of revenues to pure profits.

This distinction can be characterized exactly. Combining the profit-rate definitions yields the following decomposition of the difference between the profit measure used in the literature, $\Pi_{jt}^{\mathrm{DEU}}$, and our baseline measure, $\Pi_{jt}$:

$$\Pi_{jt} = \Pi_{jt}^{\mathrm{DEU}} - (\varrho_{jt} + \boldsymbol{\tau}_{jt} + \boldsymbol{\nabla}_{jt}) Q_{t-1} k_{jt}. \tag{B.5}$$

To quantify the importance of each component in the aggregate, we compare the two profit measures using sales weights, which are standard in the literature and therefore facilitate comparison with De Loecker et al. (2020). As shown above, applying sales weights to our profit measure yields time-series patterns that are nearly identical to those obtained under our baseline capital-weighted aggregation (denominator differs depending on which weights are used).

**Figure B.10:** Profit Rate Measures




**(a)** Comparison of Profit Rate Measures **(b)** Decomposition of the Profit Gap

*Note.* Panel (a) compares three profit-rate measures, all normalized as cumulative deviations from their 1982 values: the capital-weighted baseline profit rate, the sales-weighted profit rate following De Loecker et al. (2020), and the sales-weighted version of our baseline profit measure. Panel (b) applies the decomposition in Equation (B.5) to quantify the contributions of corporate taxation, capital gains, and capital wedges to the difference between our sales-weighted baseline profit measure and the sales-weighted profit measure following De Loecker et al. (2020).

Panel (a) of Figure B.10 plots the evolution of the sales-weighted profit rate implied by Equation (B.4). Consistent with De Loecker et al. (2020), the conventional measure implies a large increase in aggregate profit rates over the sample period, substantially larger than that implied by our baseline measure. Panel (b) of Figure B.10 decomposes the difference between our sales-weighted profit measure and the sales-weighted profit measure implied by Equation (B.4) into the contributions of capital gains, corporate taxation, and capital wedges. The figure shows that the difference is driven almost entirely by capital wedges. The substantial rise in capital wedges documented in Section 4.2.4 implies a significantly higher user cost of capital, consistent with the observed stability of the adjusted revenue-based marginal product of capital. As a result, a smaller share of revenues is attributed to pure profits, leading to a considerably more modest increase in aggregate profit rates.

## B.8 Risk Premium Measures

**Implementation details.** The implementation of the estimation of risk premia follows the approach described in Section 3.5 and uses the risk factors of Hou et al. (2015) in place of the stochastic discount factor. The estimation of risk premia follows the two-pass procedure described in Section 3.5, implemented entirely at annual frequency.

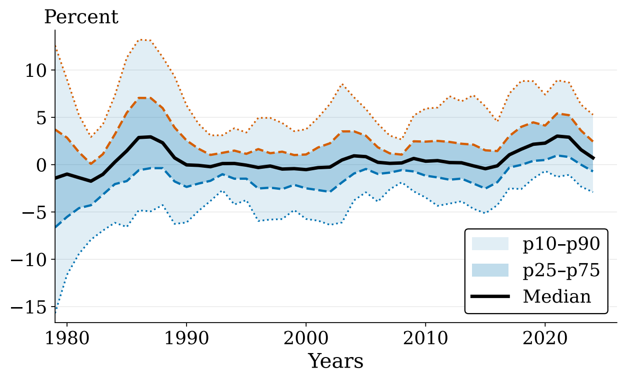
In the first pass, for each year $\tau$ we estimate firm-by-firm OLS regressions of $\mathcal{R}_{jt}^{\nabla}$ on the five annual factor returns over the backward-looking window $t \in [\tau - 5, \tau]$.[24] In the second pass, for each year $t$ we estimate a cross-sectional regression of $\mathcal{R}_{jt}^{\nabla} - r_{t-1}$ on the five estimated loadings, controlling for fixed effects of the four-digit industry and a quadratic in firm age; the coefficient vector on the loadings is the price of risk $\boldsymbol{\lambda}_t$. The firm-level risk premium is the inner product $\boldsymbol{\zeta}_{jt} = \sum_{f=1}^{5} \hat{\beta}_{jf,t}\, \hat{\lambda}_{f,t}$, that we smooth with a moving average centered on 3-year intervals to attenuate small-sample estimation error. Aggregate series weight firms by their capital stock.

**Risk premia distribution over time.** Figure B.11 reports the evolution of the cross-sectional distribution of the baseline firm-level risk premium, $\boldsymbol{\zeta}_{jt}$, over time. The figure plots the median together with the interquartile range and the 10th-90th percentile range across firms in each year. The distribution is highly dispersed, with a median close to zero, consistent with the capital-weighted average reported in the main text. At the same time, the distribution exhibits substantial heterogeneity, with a sizeable upper tail of firms facing high positive risk premia and a corresponding lower tail of firms with negative risk premia.

**Validation of the risk-premia measure.** Here we validate our measure of risk premia against two natural predictions of the model. First, we examine whether sectors with more dispersed risk premia also exhibit greater dispersion in the revenue-based marginal product of capital and revenue-based total factor productivity, as implied by theories linking risk heterogeneity to measured misallocation (e.g., David et al., 2022). Second, we test whether firms with higher risk premia exhibit higher realized returns, lower capital stocks, and lower capital-to-variable-cost ratios, consistent with the investment conditions implied by the model.

[24] Using a longer rolling window of 20-year leaves the aggregate risk-premium series essentially unchanged and results are available upon request.

**Figure B.11:** Evolution of the Cross-sectional Distribution of the Risk Premia




*Note.* The figure plots the cross-sectional 10th, 25th, 50th, 75th, and 90th percentiles of the firm-level baseline risk premium $\zeta_{jt}$ by year, with shaded bands marking the interquartile (p25-p75) and 10th-90th range.

Table B.3 confirms that cross-sectional dispersion in risk premia is strongly associated with dispersion in the revenue-based marginal product of capital and revenue-based total factor productivity, as predicted by the theory.

**Table B.3:** Risk Premium Dispersion and Misallocation

| | $\sigma(MRPK)$ (1) | $\sigma(TFPR)$ (2) |
|---|---|---|
| $\sigma(\zeta_{jt})$ | 1.428*** | 0.284*** |
| | (0.158) | (0.090) |
| *Fixed effects* | | |
| Sector | ✓ | ✓ |
| Year | ✓ | ✓ |
| Observations | 8748 | 8748 |

*Note.* This table reports regressions of the within-sector cross-sectional standard deviation of the revenue-based marginal product of capital and revenue-based total factor productivity on the within-sector cross-sectional standard deviation of risk premia. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table B.4 examines the firm-level relationship between our baseline measure of risk premia and three outcomes: cumulative stock returns, total capital, and the capital-to-variable-input ratio. Firms with higher risk premia exhibit significantly higher stock returns, lower capital stocks, and lower capital-to-variable-input ratios, consistent with the model's prediction that higher risk compensation raises the cost of capital and reduces desired capital holdings.

**Robustness.** To assess the sensitivity of our results to the choice of factor model, we re-estimate the two-stage Fama-MacBeth procedure using four alternative specifications:

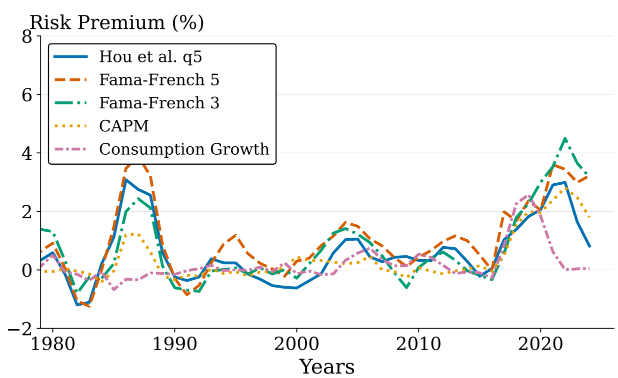
**Table B.4:** Risk Premium and Firm-Level Outcomes

| | **Cum. return** (1) | **ln** $k_{jt}$ (2) | **ln**$(k_{jt}/\ell_{jt})$ (3) |
|---|---|---|---|
| $\zeta_{jt}$ | 0.818*** | -0.818*** | -1.370*** |
| | (0.061) | (0.041) | (0.054) |
| *Fixed effects* | | | |
| Firm | ✓ | ✓ | ✓ |
| Sector-time | ✓ | ✓ | ✓ |
| Observations | 114596 | 114596 | 114596 |

*Note.* This table reports regressions of firm-level cumulative stock returns, capital stocks, and capital-to-variable-input ratios on firm-level risk premia estimated using the Hou et al. (2015) five-factor model. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

(i) Fama-French 5-Factor (Fama and French, 2015), (ii) Fama-French 3-Factor (Fama and French, 1993), (iii) CAPM, and (iv) Consumption Growth (C-CAPM).

**Figure B.12:** Risk Premium under Alternative Factor Models




*Note.* This figure plots the capital-weighted aggregate risk premium estimated under five alternative factor models.

Figure B.12 plots the capital-weighted aggregate risk premium under each specification. The five measures exhibit broadly similar time-series dynamics. Although some specifications display less cyclical variation than others, all imply a similar long-run evolution, indicating that the broad stability of risk premia over time is not driven by the particular set of risk factors used in the estimation.

Table B.5 reports the full pairwise correlation matrix of firm-level risk premia estimated using the five alternative factor models. Overall, the measures are positively correlated with one another, indicating that they capture similar dimensions of risk despite relying on different underlying risk factors.

**Table B.5:** Correlation of Firm-Level Risk Premia across Factor Models

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| (1) *Hou et al. q5* | 1.000 | | | | |
| (2) *Fama-French 5* | 0.683 | 1.000 | | | |
| (3) *Fama-French 3* | 0.551 | 0.616 | 1.000 | | |
| (4) *CAPM* | 0.364 | 0.435 | 0.644 | 1.000 | |
| (5) *Consumption Growth* | 0.322 | 0.422 | 0.435 | 0.407 | 1.000 |

*Note.* This table reports the pairwise correlations among firm-level risk premia estimated using five alternative factor models.

## B.9 Drivers of Capital Wedge

**Cross-sectional distribution.** Figure B.13 reports the evolution of the cross-sectional distribution of the firm-level capital wedge $\nabla_{jt}$, showing the median together with the interquartile and 10%–90% ranges across firms by year. The dispersion is substantial throughout the sample.

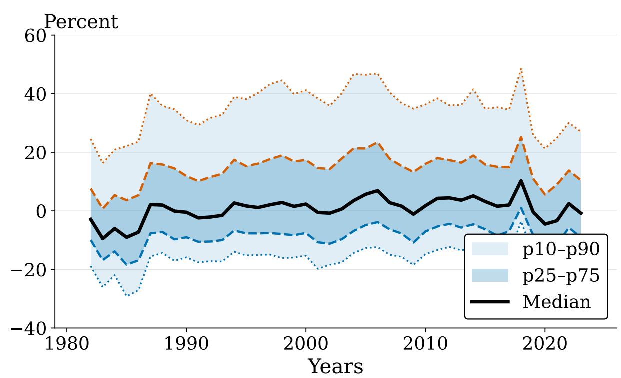



**Figure B.13:** Evolution of the Cross-sectional Distribution of the Capital Wedge $\nabla_{jt}$

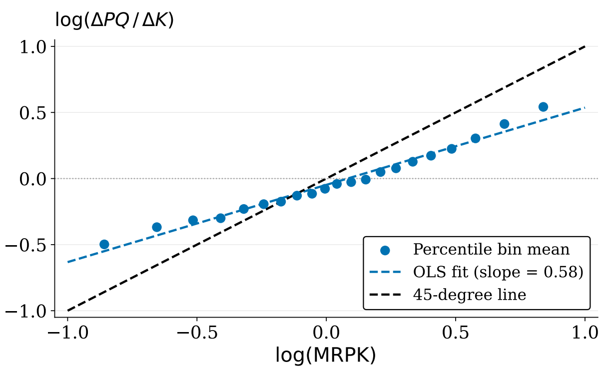
*Note.* The figure plots the cross-sectional 10th, 25th, 50th, 75th, and 90th percentiles of the firm-level capital wedge $\nabla_{jt}$ by year, with shaded bands marking the interquartile (p25–p75) and 10%–90% ranges. The series is reported in percent. Sample: Compustat firm-years, 1982–2024.

**Measurement error.** We assess the extent of measurement error in our estimates of capital wedges using the approaches proposed by Bai et al. (2024) and Bils et al. (2021).

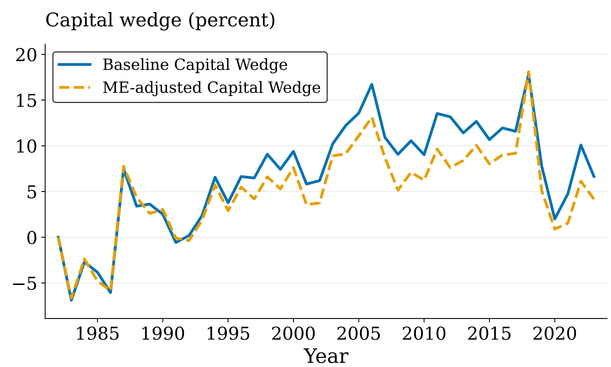
The approach of Bai et al. (2024) exploits the fact that the revenue-based marginal product of capital can be approximated by the change in output relative to the change in capital input, $MRPK \approx \Delta pq/\Delta k$. This first-difference measure provides an alternative estimate of the revenue-based marginal product that is less sensitive to persistent measurement error. In the absence of measurement error, the baseline and first-difference measures should be perfectly correlated; conversely, if the observed variation were driven entirely by measurement error, the two measures would be uncorrelated.

Panel (a) of Figure B.14 compares our baseline measure with the corresponding first-difference estimate. Both variables are demeaned by 4-digit industry-by-year means and grouped into 25 quantile bins. The two measures are strongly positively correlated, indicating that measurement error accounts for only a limited fraction of the observed variation in $\boldsymbol{\nabla}_{jt}$. At the same time, the estimated slope is below unity, suggesting the presence of some measurement error. We now quantify its magnitude.

**Figure B.14:** Measurement Error in the Revenue-Based Marginal Product of Capital




**(a)** Mismeasurement




**(b)** ME-Adjusted Capital Wedge

*Note.* Panel (a) plots binned means (25 quantiles) of the log ratio of sales changes to capital changes against the demeaned log revenue-based marginal product of capital. Both variables are residualized with respect to 4-digit industry-by-year means. The dashed blue line reports the OLS fit, while the dashed black line denotes the 45-degree line. Panel (b) plots the baseline capital-weighted capital wedge and its measurement-error-adjusted counterpart, both expressed as cumulative deviations from their 1982 values.

To quantify the extent to which the rise in $\boldsymbol{\nabla}_{jt}$ reflects measurement error rather than genuine variation in revenue-based marginal products, we follow Bils et al. (2021). Their approach exploits the regression

$$\Delta \log p_{jt} q_{jt} = \alpha_\kappa + \beta_\kappa \, \Delta \log k_{jt} + \varepsilon_{jt}, \tag{B.6}$$

where $\Delta \log pq$ and $\Delta \log k$ denote firm-level log changes in sales and capital, respectively, and $\kappa$ indexes the cell defined by year, 2-digit sector, and the firm's $MRPK$ quantile within that year-sector group. Intuitively, if cross-sectional variation in $MRPK$ is driven by additive measurement error, firms with higher observed $MRPK$ should exhibit a lower elasticity of sales with respect to capital. Bils et al. (2021) show that $\beta_\kappa$ identifies the extent of additive measurement error, allowing us to construct the corrected measure $\beta_{\kappa(j,t)} \cdot MRPK_{jt}$. We then recover the corresponding measurement-error-adjusted capital wedge by substituting the corrected $MRPK$ into our decomposition.

Panel (b) of Figure B.14 compares the capital-weighted aggregate baseline wedge with its measurement-error-adjusted counterpart, both expressed as cumulative deviations from 1982. Correcting for measurement error lowers the level of the wedge, but leaves its long-run evolution largely unchanged. Thus, while measurement error contributes to the level of capital wedges, it accounts for only a small fraction of their observed increase over time.

# C Findings Appendix

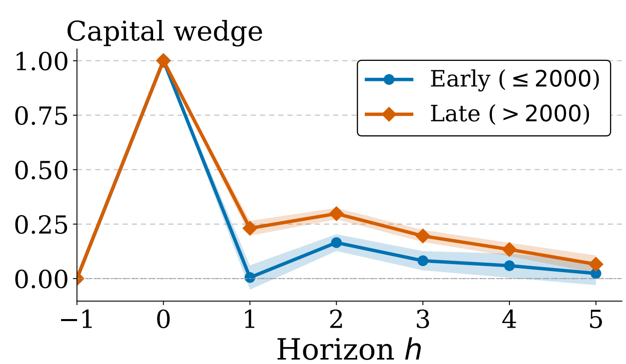
## C.1 Aggregate Trends

We assess the robustness of the finding that capital wedges are the primary driver of the divergence between the measured return on capital and the risk-free rate to alternative measurement choices. In particular, we consider alternative production function estimators, markup measures, and initial conditions for intangible capital (Appendix B.7); alternative estimates of risk premia (Appendix B.8); alternative investment deflators (Appendix B.3); and alternative calibrations of investment deductibility rates (Appendix B.5). Overall, our conclusions are robust to all alternative measurement choices considered. In every specification, capital wedges remain the primary driver of the divergence, accounting for no less than 57 percent of the observed increase in the return gap.

## C.2 Additional Firm Dynamics and Capital Wedges Results

**Capital wedge impulse response.** We report the impulse response of the capital wedge, $\nabla_{jt}$, to the same quasi-shock considered in the main text. Figure C.1 presents the response separately for the pre- and post-2000 periods. Consistent with the decomposition results of rising capital wedges and the documented slowdown in capital accumulation, the response of the capital wedge is more persistent in the later period.

**Figure C.1:** Impulse Response of the Capital Wedge $\nabla_{jt}$, Early vs. Late Samples




*Note.* The figure plots the impulse response of the firm-level capital wedge, $\nabla_{jt}$, to the quasi-shock described in Section 5.3, separately for the pre- and post-2000 samples. Shaded bands denote 95% confidence intervals based on firm-clustered standard errors.

**Case studies.** Here we report further details regarding the case studies discussed in the main text.

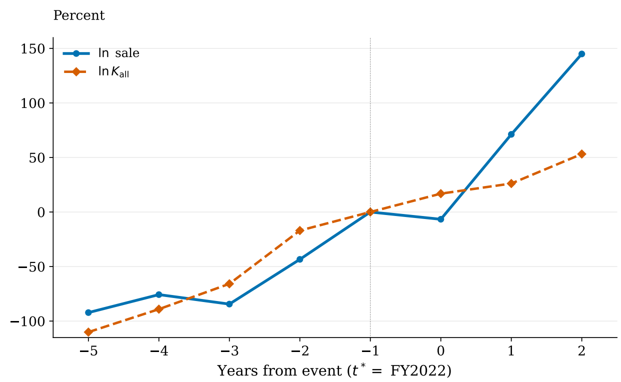
**Table C.1:** Robustness of the Main Decomposition to Alternative Measurement Choices

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| **Panel A:** *Production Function Estimator, Intangible Capital Construction* | | | | | | | |
| $R - r$ | 9.19 | 9.19 | 9.19 | 9.19 | 9.19 | 8.93 | 9.18 |
| *Capital Wedge* | 6.74 | 5.28 | 7.75 | 6.97 | 6.12 | 6.01 | 7.13 |
| *Profits* | 0.99 | 2.11 | -0.80 | 0.19 | 2.06 | 0.64 | -1.16 |
| *Risk Premium* | 1.83 | 2.17 | 2.62 | 2.41 | 1.38 | 2.50 | 2.20 |
| *Capital Gains* | 0.56 | 0.56 | 0.56 | 0.56 | 0.56 | 0.56 | 0.56 |
| *Taxation* | -0.93 | -0.93 | -0.93 | -0.93 | -0.93 | -0.78 | -0.93 |
| **Panel B:** *Risk Premia Measures* | | | | | | | |
| $R - r$ | 9.19 | 9.19 | 9.19 | 9.19 | 9.19 | | |
| *Capital Wedge* | 8.11 | 7.02 | 6.42 | 6.74 | 8.23 | | |
| *Profits* | 0.98 | 0.98 | 0.99 | 0.99 | 0.98 | | |
| *Risk Premium* | 0.48 | 1.56 | 2.16 | 1.83 | 0.36 | | |
| *Capital Gains* | 0.56 | 0.56 | 0.56 | 0.56 | 0.56 | | |
| *Taxation* | -0.93 | -0.93 | -0.93 | -0.93 | -0.93 | | |
| **Panel C:** *Investment Deductibility, $\delta_{x,t}$* | | | | | | | |
| $R - r$ | 9.19 | 9.19 | 9.19 | 9.19 | 9.19 | | |
| *Capital Wedge* | 6.93 | 6.84 | 6.74 | 6.61 | 6.51 | | |
| *Profits* | 0.81 | 0.89 | 0.99 | 1.10 | 1.23 | | |
| *Risk Premium* | 2.09 | 1.97 | 1.83 | 1.70 | 1.51 | | |
| *Capital Gains* | 0.56 | 0.56 | 0.56 | 0.56 | 0.56 | | |
| *Taxation* | -1.21 | -1.07 | -0.93 | -0.78 | -0.63 | | |
| **Panel D:** *Capital Price Deflator* | | | | | | | |
| $R - r$ | 9.19 | 9.53 | | | | | |
| *Capital Wedge* | 6.74 | 10.41 | | | | | |
| *Profits* | 0.99 | 1.41 | | | | | |
| *Risk Premium* | 1.83 | 0.64 | | | | | |
| *Capital Gains* | 0.56 | -1.54 | | | | | |
| *Taxation* | -0.93 | -1.39 | | | | | |

*Notes.* **Panel A** reports robustness to alternative production function estimators, measures of intangible capital, and markup measures (Appendix B.8). Column (1) reports the baseline system GMM estimator; column (2) system GMM without the first-stage correction; column (3) system GMM with the measurement-error correction; column (4) the ACF estimator; column (5) the ACF estimator with the oligopoly instrument; column (6) the alternative intangible-capital measure with non-zero initial intangible capital; and column (7) the accounting-based markup measure. **Panel B** reports robustness to alternative risk-premia measures based on alternative risk factors (Appendix B.7). Column (1) uses the CAPM; columns (2) and (3) use the Fama-French three- and five-factor models; column (4) uses the $q$-factor model (baseline); and column (5) uses the consumption-growth model. **Panel C** varies the calibrated investment-deductibility parameter $\delta_{x,t}$ (Appendix B.5). Column (1) reports results for $\delta_{x,t} = 0$; column (2) reports results for $\delta_{x,t} = 0.10$; column (3) reports results for $\delta_{x,t} = 0.20$ (baseline); column (4) reports results for $\delta_{x,t} = 0.30$; and column (5) reports results for $\delta_{x,t} = 0.40$. **Panel D** uses alternative capital price deflators (Appendix B.3). Column (1) reports results using the Törnqvist capital-weighted deflator (baseline), while column (2) reports results using the standard investment-weighted deflator. Each cell reports the 1982–2024 average of the cumulative deviation of the corresponding component in Equation (2) from its 1982 value. The baseline specification is marked with †.

- *NVIDIA (2023).* As a concrete illustration of the post-2017 disconnect between revenue growth and capital accumulation, Figure C.2 plots the evolution of NVIDIA's net sales and total capital stock from fiscal year 2017 through 2024. Following the

**Figure C.2:** NVIDIA: Sales and Total Capital, 2022 Event



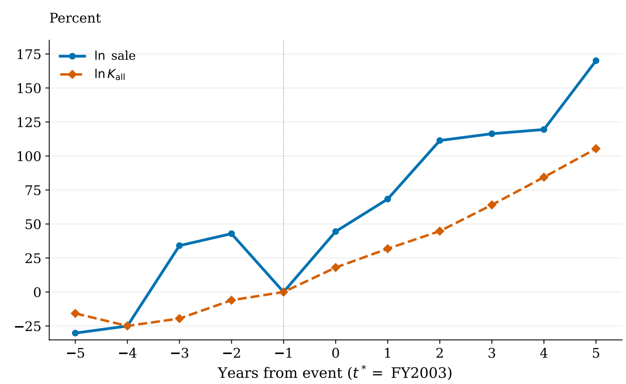

*Note.* The figure plots NVIDIA's sales and total capital stock around 2022.

  diffusion of generative AI after the release of ChatGPT in late 2022, demand for AI compute rose sharply and NVIDIA's revenues expanded at unprecedented rates. Its capital stock, by contrast, increased comparatively little. This divergence reflects, at least in part, the intangible-intensive nature of NVIDIA's business model. Scaling AI-related activity required relatively limited expansion of tangible production capacity but substantial investment in intangible assets, including software, platforms, and developer ecosystems. Because these investments rely heavily on organizational capital, specialized human capital, and knowledge creation, they are often slower to scale than conventional physical capital.

- *EOG Resources, Inc. (2003)* A further illustration of the post-2000 disconnect between revenue growth and capital accumulation is provided by EOG Resources in the early 2000s, as shown in Figure C.3. Benefiting from rising natural gas prices and the shale gas boom, EOG experienced a substantial increase in revenues that was not matched by a comparable expansion in capital. In this case, the slower growth of capital relative to sales appears to have reflected a deliberate managerial strategy of controlling capital expenditures in order to maximize returns on capital and cash flow generation. Consistent with this, EOG maintained a hurdle rate of approximately 10.2%, defined as the minimum rate of return required before undertaking an investment project, substantially above its reported cost of capital of 7.9% between 2003-2008 (Gormsen and Huber, 2023, 2024).

- *Devon Energy Corporation (1992).* Here, we provide an example of firm expansion in the pre-2000 era. In July 1992, Devon completed a $130 million acquisition of a substantial portfolio of Permian Basin properties—one of four Permian transactions undertaken between 1987 and 1995 and the most transformative. The acquisition more than doubled Devon's annual sales, from $48 million in 1991 to $113 million in 1992, while book capital increased by 63% in the same year (see Figure C.4 in Appendix C.2). Unlike the post-2000 episodes discussed above, rapid revenue growth was accompanied by substantial capital accumulation. This pattern reflects a growth strategy centered on the acquisition and development of productive assets. As Devon's FY1995 Form 10-K states, the firm pursued "a two-pronged strategy of acquiring producing properties and engaging primarily in development drilling and limited exploration activities," under which expansion was closely tied to the accumulation of capital.

**Figure C.3:** EOG: Sales and Total Capital, 2003 Event



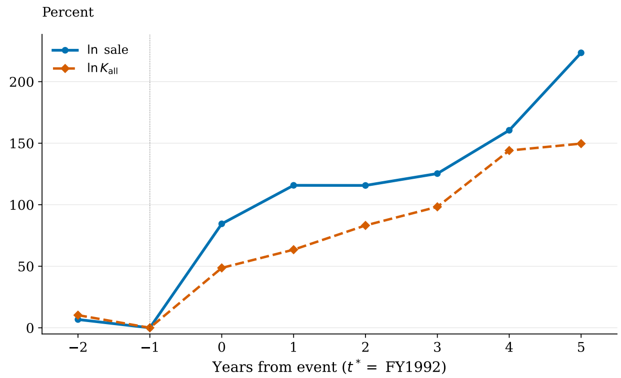

*Note.* The figure plots EOG's sales and total capital stock around 2003.

## C.3 Rising Intangible Capital and Its Consequences

**Rising intangible intensity.** We document the evolution of intangible intensity, defined as the share of intangible capital in total capital. Figure C.5 plots the average intangible intensity by year and confirms the well-documented rise in intangible capital reported in the literature. Intangible intensity increases from roughly 35% in 1982 to about 55% by the end of the sample. Consistent with this trend, average intangible intensity rises from 44.4% before 2000 to 53.8% after 2000.

**The implications of rising intangible capital: a shift-share analysis.** To assess how much of the post-2000 decline in capital accumulation following a capital-wedge quasi-

**Figure C.4:** Devon Energy: Sales and Total Capital, 1992 Event




*Note.* The figure plots Devon's sales and total capital stock around 1992.

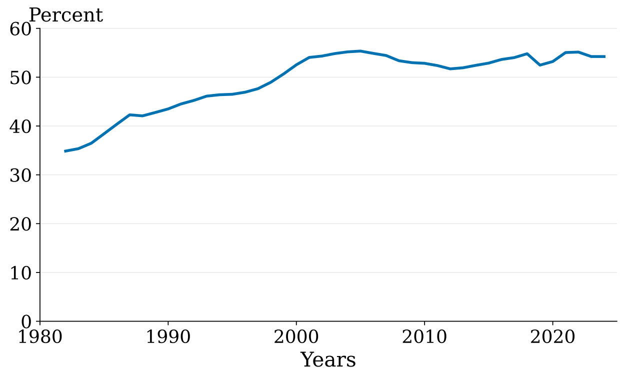



**Figure C.5:** Intangible Intensity

*Note.* The figure plots the cross-sectional average intangible-capital intensity, $k^I_{jt}/k_{jt}$, by year.

shock can be attributed to the rising importance of intangible capital, we perform a shift-share decomposition. Let intangible intensity be defined as $s_{jt} \equiv k^I_{jt}/k_{jt}$. Since total capital growth can be approximated as a share-weighted average of the growth rates of tangible and intangible capital, $\Delta \log k_{jt} \approx s_{jt} \Delta \log k^I_{jt} + (1 - s_{jt}) \Delta \log k^T_{jt}$, changes in the estimated impulse response of total capital can be decomposed into changes in the responses of its tangible and intangible components and changes in their relative shares.

Specifically, let $\overline{\beta}$ denote the estimated average response of total capital across the different horizons $h$, and let $\overline{\beta}^I$ and $\overline{\beta}^T$ denote the corresponding responses of intangible and tangible capital, respectively. Then the change in the average response between the pre-2000 ($E$) and post-2000 ($L$) periods can be written as

$$\overline{\beta}_L - \overline{\beta}_E \approx \bar{s} \left( \overline{\beta}^I_L - \overline{\beta}^I_E \right) + (1 - \bar{s}) \left( \overline{\beta}^T_L - \overline{\beta}^T_E \right) + (\bar{s}_L - \bar{s}_E) \left( \overline{\beta}^I - \overline{\beta}^T \right). \tag{C.1}$$

The left-hand side captures the change over time in the estimated average response of total capital. The first term on the right-hand side measures the contribution of changes in the response of intangible capital, the second term captures the contribution of changes in the response of tangible capital, and the final term measures the contribution of the shift in capital composition toward intangible assets.

**Table C.2:** Shift-Share Decomposition of the Post-2000 Slowdown in Capital Accumulation

**Panel A.** *Intangible Intensity and Tangible and Intangible Capital Average Responses*

| | **Early** | **Late** | **Mean** | $\boldsymbol{\Delta_{L-E}}$ |
|---|---|---|---|---|
| *Intangible share, $s$* | +0.4440 | +0.5380 | +0.4910 | +0.0940 |
| *Tangible response, $\overline{\beta}^T$* | +0.2918 | +0.2102 | +0.2510 | -0.0817 |
| *Intangible response, $\overline{\beta}^I$* | +0.1870 | +0.1585 | +0.1728 | -0.0285 |

**Panel B.** *Shift-Share Decomposition*

| | **Contribution** |
|---|---|
| *Within-tangible,* $(1-\bar{s})\left(\overline{\beta}_L^T - \overline{\beta}_E^T\right)$ | -0.0416 |
| *Within-intangible,* $\bar{s}_E\left(\overline{\beta}_L^I - \overline{\beta}_E^I\right)$ | -0.0140 |
| *Share shift,* $(\bar{s}_L - \bar{s}_E)\left(\overline{\beta}^I - \overline{\beta}^T\right)$ | -0.0074 |
| *Approximation error* | +0.0100 |
| *Total change,* $\overline{\beta}_L - \overline{\beta}_E$ | -0.0530 |

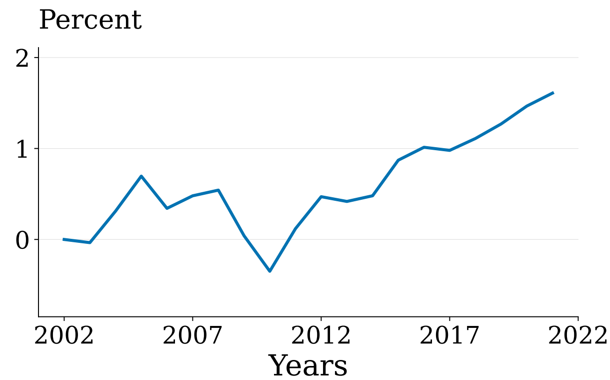
*Notes.* The table presents a shift-share decomposition of the slowdown in the response of total capital to a capital wedge quasi-shock. **Panel A** reports average intangible intensity together with the average responses of tangible and intangible capital in the pre- and post-2000 periods, as well as the corresponding differences. **Panel B** reports the implied shift-share decomposition of the slowdown in the total capital response and the associated approximation error.

Table C.2 reports the results. The response of total capital to a capital-wedge quasi-shock declines by 0.053 log points between the pre- and post-2000 periods. Approximately 40 percent of this decline reflects the growing importance of intangible capital: the rise in intangible intensity accounts for 0.0074 log points, while the decline in the responsiveness of intangible capital accounts for a further 0.0140 log points.

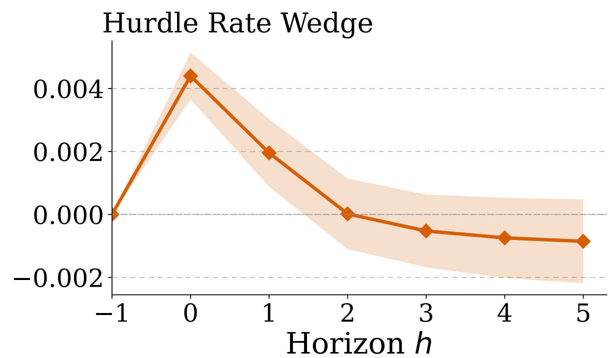
## C.4 The Hurdle Wedge

Following Gormsen and Huber (2023), the hurdle rate wedge is defined as the difference between a firm's hurdle rate and its perceived cost of capital. A positive hurdle rate wedge implies that managers require a return on new investment that exceeds their perceived cost of financing, thereby slowing capital accumulation even when growth opportunities are strong.

**Figure C.6:** The Hurdle Rate Wedge: Trend and Responsiveness




**(a)** Aggregate Hurdle Rate Wedge




**(b)** Hurdle Rate Wedge

*Note.* Panel (a) plots the cumulative change in the capital-weighted aggregate hurdle rate wedge constructed from the Gormsen and Huber (2023) data, available for the period 2002–2021. Panel (b) reports the local projection impulse response of the firm-level hurdle rate wedge to a capital wedge quasi-shock. Shaded bands denote 95% confidence intervals based on standard errors clustered at the firm level.

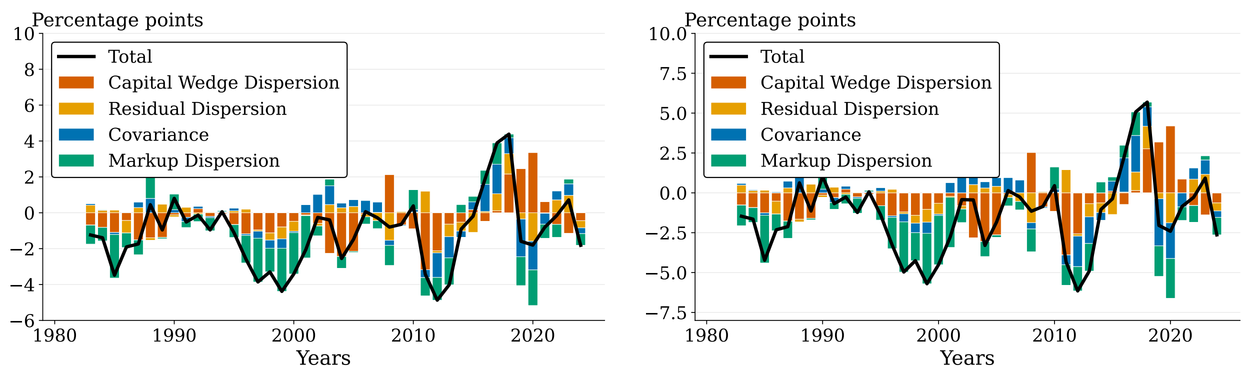
Panel (a) of Figure C.6 plots the capital-weighted aggregate hurdle rate wedge. The series rises by approximately 1.61 percentage points between 2002 and 2021, the period for which these data are available. Panel (b) shows that this pattern is also evident at the firm level. Re-estimating the local projection specification from the main text with the firm-level hurdle rate wedge as the outcome variable, we find that a capital wedge quasi-shock leads to an increase in firms' hurdle rate wedges. Because hurdle rate data are available only from 2002 onward, the analysis is restricted to the post-2000 period.

## C.5 Aggregate productivity

**Implementation details.** The capital wedge $\boldsymbol{\nabla}_{jt}$ is an additive component of the user cost and takes nonpositive values for some firm-years; therefore, we do not transform it logarithmically. Instead, the split of $\mathbb{V}(\log ARPK_{jt})$ into wedge-driven and residual components uses the share $s_t^{\nabla}$, computed as the capital-weighted average across sectors of the $R^2$ from sector-year regressions of $ARPK_{jt}$ on $\boldsymbol{\nabla}_{jt}$ in levels; the share is bounded in $[0, 1]$ by construction.

In Figures C.7a and C.7b, we highlight the different sources of TFP losses under alternative values of the elasticity of substitution, $\sigma$. We summarize these findings in Table C.3, which shows that our framework predicts a drag between 0.8–1.4 pp per year on TFP growth, depending on the assumed elasticity of substitution $\sigma$. The growth of output-wedge (markup) dispersion and capital-wedge dispersion are the major drivers of the drag on aggregate productivity; the covariance and residual terms are small contributors. The Pre-COVID window is uniformly *more* negative than the whole-period average.

**Figure C.7:** TFP Growth




**(a)** $\sigma = 4$ **(b)** $\sigma = 5$

*Note.* The figure plots the centred 3-year moving average of the contribution of changes in misallocation to TFP growth, in percentage points per year, for two alternative values of the elasticity of substitution: $\sigma = 4$ in Panel (a) and $\sigma = 5$ in Panel (b) (the baseline $\sigma = 3$ is shown in Figure 9a). Positive values indicate years in which MRPK misallocation eased and thus contributed positively to TFP growth.

**Table C.3:** Average annual contributions to TFP-growth loss from misallocation

| | $\sigma = 3$ | | $\sigma = 4$ | | $\sigma = 5$ | |
|---|---|---|---|---|---|---|
| Component | Whole | Pre-COVID | Whole | Pre-COVID | Whole | Pre-COVID |
| Total | -0.842 | -0.883 | -1.110 | -1.155 | -1.413 | -1.461 |
| Output-wedge dispersion | -0.465 | -0.455 | -0.640 | -0.622 | -0.840 | -0.813 |
| Covariance | 0.018 | 0.044 | 0.033 | 0.073 | 0.051 | 0.108 |
| Capital-wedge dispersion | -0.365 | -0.445 | -0.458 | -0.564 | -0.563 | -0.696 |
| Residual dispersion | -0.030 | -0.027 | -0.045 | -0.042 | -0.062 | -0.061 |

*Note.* Values are averages of the 3-year centered moving average of the yearly TFP-growth contribution, in percentage points per year. A negative value indicates a contribution that reduces measured TFP growth. Whole-period is 1983–2024; Pre-COVID is 1983–2019.